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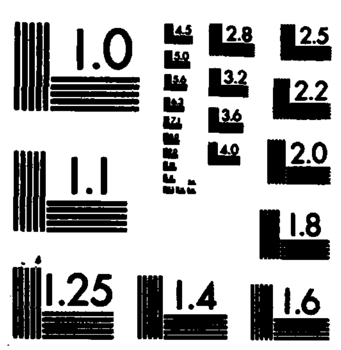


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# DEVELOPMENT OF A MODEL FOR HUMAN OPERATOR LEARNING IN CONTINUOUS ESTIMATION AND CONTROL TASKS

*WILLIAM H. LEVISON*
*BOLT BERANEK AND NEWMAN INC.*

DECEMBER 1983







AIR FORCE AEROSPACE MEDICAL RESEARCH LABORATORY
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AFAMRL-TR-83-088

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FOR THE COMMANDER

CHARLES BATES, JR.
Director, Human Engineering Division
Air Force Aerospace Medical Research Laboratory

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This research was directed toward the development of an analytic tool for the design of training procedures and the assessment of trainee performance in the kinds of monitoring, decision, and control tasks required for flight management. Manual control data obtained in previous AFAMRL Laboratory studies was analyzed with regard to learning behavior. This analysis consisted of three steps: (1) model analysis with the optimal control pilot model (OCM) to determine the relations between stages of training and independent "pilot-related" model parameters; (2) tests of some hypotheses concerning the underlying effects of training on control-strategy development; and (3) preliminary analysis to explore relationships between the perceptual cueing environment and the pilot's internalized representation ("internal model") of the task situation. The results of the analysis suggest that continued

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practice on the tracking task leads to a more precise, consistent, and linear (i.e., less 'noisy') type of response behavior, and to an improved internal model. Analytic results further suggest that, if the OCM is modified to account for the pilot's ability to construct his internal model, the model should be able to predict the effects of the task structure (including plant dynamics, input spectra, and cueing environment) on the rate at which (and degree to which) the human operator develops his estimation and control strategies.

11. Title

Development of a Model for Human Operator Learning in Continuous Estimation and Control Tasks

## PREFACE

The research summarized in this report was performed by Bolt Beranek and Newman Inc. for the Air Force Aerospace Medical Research Laboratory under Contract No. F33615-81-C-0517. Mr. Andrew M. Junker was the technical monitor for the Air Force; Dr. William H. Levison served as Principal Investigator for Bolt Beranek and Newman Inc.

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# 1. INTRODUCTION AND SUMMARY

## 1.1 Objectives

Because the cost of airborne operations has increased dramatically in recent years, ground-based simulators have come to play an ever-increasing role in the training of Air Force pilots. Consequently, one of the major forces (if not the major force) driving training costs is the number of trainee and instructor hours required to achieve desired proficiency in the training simulator. Procedures that can improve training efficiency have the potential to improve the flying skills of Air Force pilots while substantially reducing training costs.

Ground-based simulators have an advantage over airborne trainers in that the informational (or perceptual) environment in which the trainee operates may, within limitations of cost, be designed to optimize training. In particular, there exists the option to artificially enhance cues that are normally present in actual flight -- and, perhaps, to create additional cues not present in flight -- in order to increase training efficiency. At present, however, there is no detailed, validated theory that allows one to predict, from knowledge of the informational environment, the degree and rate of acquisition of flying skills.

The research summarized in this study was directed toward the long-term objective of developing an analytic tool for the design of training procedures and the assessment of trainee performance in the kinds of monitoring, decision, and control tasks required for flight management. A more specific goal was to extend the optimal control model (OCM) for pilot/vehicle systems into a predictive tool that relates the acquisition of continuous estimation and control strategies to the perceptual cueing environment.

Full-scale development of a model for control-strategy development was beyond the scope of this study. As a first step in this direction, the following three major tasks were completed:

1. reanalysis of existing manual control data to determine the effects of practice on independent pilot model parameters,
2. exploration of various hypotheses concerning information-processing deficits early in suggested training, and
3. feasibility testing of an approach suggested for further model development, in which control-strategy development is related to development of the operator's "internal model" of the task environment.

In the process of performing the first task (model analysis), we explored in some detail the techniques adopted for performing a statistical analysis of model parameters. Results of this parametric study are contained largely in the Appendix for readers interested in methodological detail.

## 1.2 Approach

Model analysis performed in this study employed the existing optimal control model for pilot/vehicle systems. This model was considered well-suited to the long-term modeling effort for a number of reasons:

1. The optimal control model provides agreement with data for a wide variety of control tasks, including time-varying control situations.

2. The model incorporates many features that derive from or are related to known human performance characteristics.

3. The concepts of internal models and operator response variability, which are integral to the definition of control strategy in the OCM, are extremely appropriate in the context of learning.

4. The model is capable of dealing with cue utilization in a direct fashion, and has been used to model successfully the influence of whole-body platform motion on asymptotic tracking performance.

The following criteria were adopted to guide the modeling effort pursued in this study, and they are recommended for further model development. First, the model must account for important trends found in the existing relevant data base. This includes matching the effects of various aspects of the task environment on both learning rates and asymptotic performance (i.e., how fast the subject learns, and how well he learns).

Second, if one is to develop a predictive model for learning behavior, the model should have a structure and parameterization that facilitate extrapolation to new situations. Such extrapolation is enhanced if we can (1) determine a minimal set of independent model parameters that applies over the tasks of interest, and (2) partition independent parameters into task-related and operator-related categories.

Finally, model structure should be compatible with what is known about human capabilities and limitations. That is, it should "make sense".

### 1.3 Organization of this Report

The results of this study are presented at three levels of detail. The concluding section of this chapter provides an extended summary of the research effort, highlighting key results. Chapters 2 through 5 are recommended to readers who wish to understand the basis for the results presented in the Summary. Finally, two Appendices provide further details concerning the background material, the results, and the analysis methodology.

Chapter 2 -- Background -- is devoted to three topics: (1) a review of some relevant work in skill acquisition; (2) a review of key features of the optimal control model, including procedures for identifying and testing independent model parameters; and (3) a review of some evidence that suggests a relationship between the task environment and the fidelity of the operator's internal model of this environment.

Chapters 3-5 summarize, respectively, the results of the principal tasks accomplished in this study: (1) analysis of practice effects on pilot response behavior, (2) hypothesis testing, and (3) an exploratory study of an approach for relating learning to internal model development. Appendix A contains supplemental analysis pertaining to some of the background material presented in Chapter 2. Appendix B contains data for individual subjects along with data relating to methodological development.

### 1.4 Summary

The optimal control pilot/vehicle model used throughout this study partitions the human operator's input/output behavior as shown in the diagram of Figure 1-1. The operator obtains certain task-relevant perceptual inputs, which are assumed to be degraded by time delay and "noise" to account for various information-processing limitations of the human. The time delay reflects neural conduction times and other sources of pure transport delay. The observation noise mathematically accounts for various sources of response randomness and nonlinear response behavior ("pilot remnant"); for well-trained subjects provided with optimal control and display environments, the observation noise identified in simple laboratory tracking tasks appears to reflect a limitation on the signal/noise ratio with which the operator can process information.

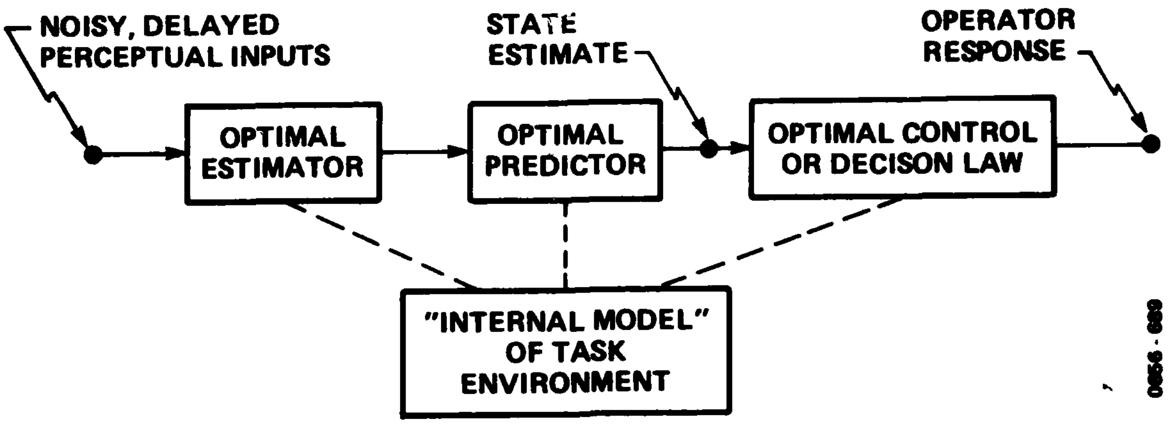



Figure 1-1. Structure for Baseline Model of Operator Response Strategy

The "optimal estimator" and "optimal predictor" elements of the model represent the operator's (presumed) attempts to best reconstruct the current "state" of the system he is monitoring. An optimal decision or control law operates on this state estimate to provide the appropriate response. In the case of a control task, the optimal control law includes a first-order lag -- characterized by the "motor time constant" -- to reflect both subjective and physiologic constraints on operator response bandwidth.

Imbedded in the model structure of Figure 1-1 is an "internal model" of the task environment which accounts for all the correlations among system variables. This internal model is generally configured to reflect faithfully the statistics of the task environment, but this assumption must be challenged when we consider tasks in which vehicle dynamics contain significant lags, and/or subjects are incompletely trained.

Figure 1-2 shows that a fixed set of independent, or "pilot-related" model parameters can yield a good match to operator frequency response (pilot gain, phase shift, and "remnant" spectrum) for a significant range of laboratory tracking tasks. If this range is extended by increasing system lags, however, we begin to see a degradation in certain "pilot parameters" as shown in Figure 1-3. Detailed analysis of these results suggests that changes in the independent model parameters reflect limitations on the operator's information-processing capabilities that have not been heretofore explicitly identified -- such as imperfections in the operator's internal model of the task environment. Thus, the desired separation of operator- and task-related model parameters has not been fully realized. Future OCM development undertaken to account for learning behavior should address this issue.

The effects of practice on average operator frequency response are shown in Figure 1-4 for three different subject populations, operating in different task environments. Similar practice trends were found: performance early in practice, relative to near-asymptotic performance, was characterized by lower pilot gain, minimal differences in phase shift, and higher remnant. Model analysis, the results of which are summarized in Figure 1-5, showed that both the average noise/signal ratio and the motor time constant decreased over the course of the training phase. Practice-related changes were relatively greater and statistically more significant for the noise parameter. These model results were obtained without constraints on the allowable changes in model parameters.

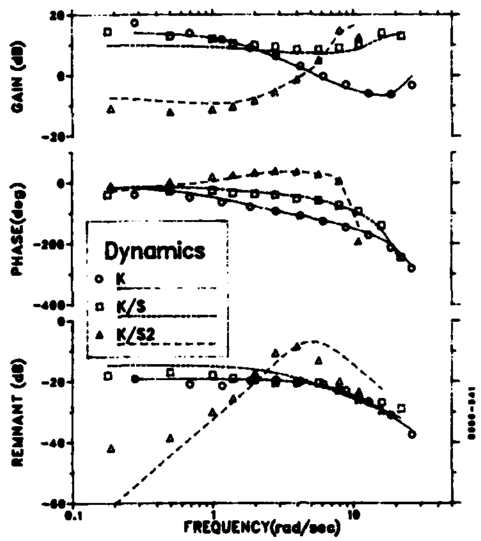



Figure 1-2. Fixed-Parameter Match to Three Tracking Tasks

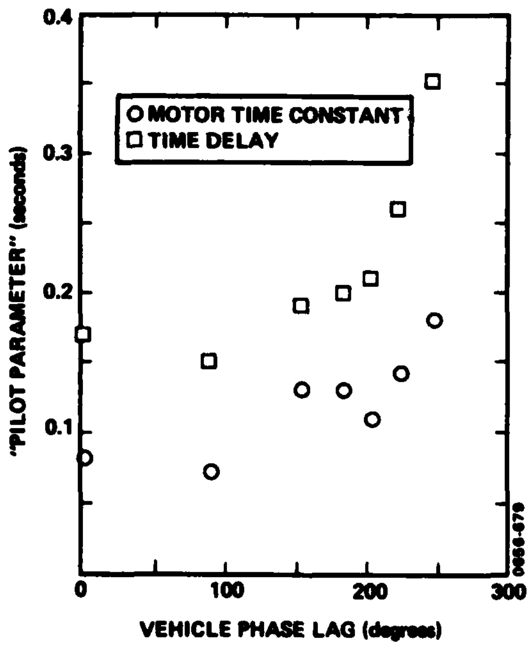
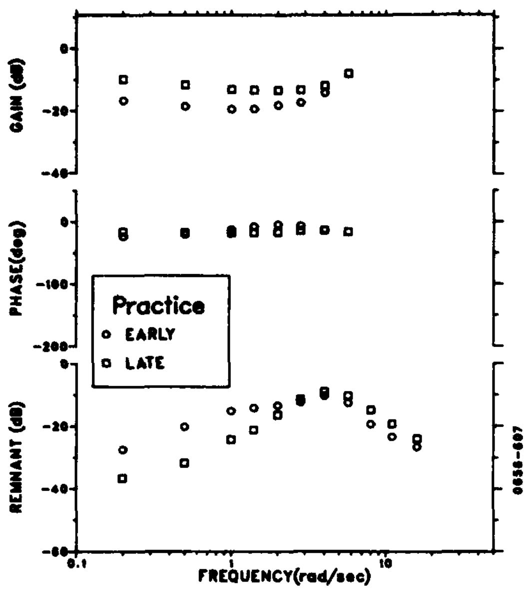
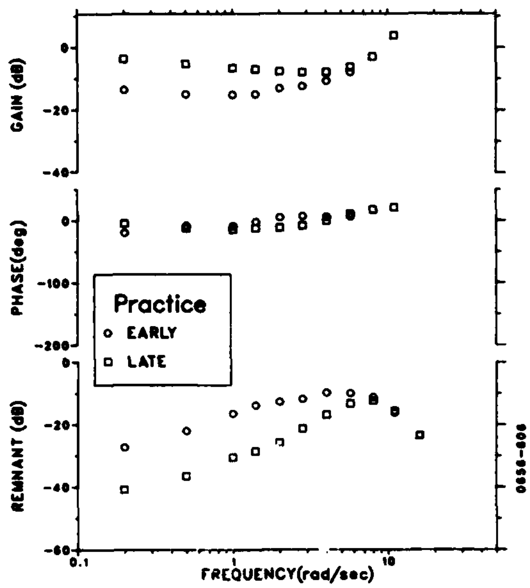



Figure 1-3. Effects of Task Complexity on Independent Model Parameters

a) Stable Plant, Fixed Base




b) Stable Plant, Moving Base




c) Unstable Plant

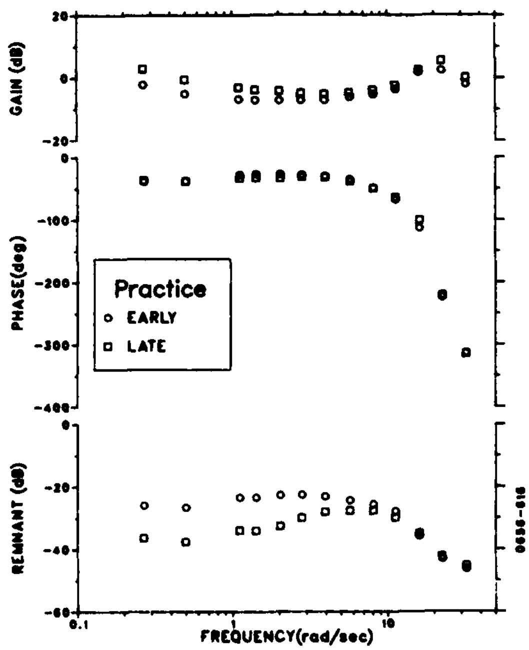



Figure 1-4. Effects of Practice on Average Pilot Frequency Response

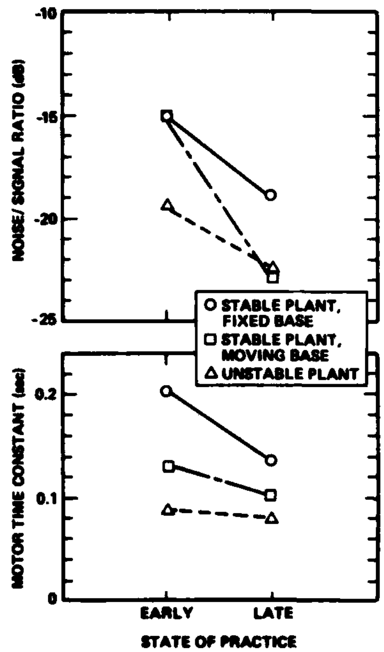



Figure 1-5. Effects of Practice on Independent Model Parameters

This data base was subsequently reanalyzed, this time with constraints imposed to reflect certain hypotheses concerning the process of skill acquisition. The goal here was to characterize practice effects in a manner that was parsimonious and yet applicable to a predictive model for learning.

We tested, individually, the hypotheses that practice effects could be accounted for (1) solely by a reduction in observation noise/signal ratio, (2) solely by an improving ability to utilize rate cues, (3) solely by an improving internal model of the tracking input, and (4) by a combined reduction in noise/signal ratio and improved internal tracking-input model.

Figure 1-6 shows that we can reject simple hypotheses concerning use of rate information and internal model changes, at least as they apply to the data base explored in this study. The observation noise hypotheses provide the best simple explanation for practice effects, and a somewhat closer match is obtained if we consider the combined effects of changes in observation niose and internal model.

Because of the substantial mathematical development that would have been required, it was beyond the scope of this study to explore hypotheses concerning practice-related changes in the operator's internal model of the simulated vehicle dynamics, at least within the framework of the OCM. Instead, a simplified analysis was conducted to demonstrate that, were such a model development to be undertaken, it could be expected to yield reasonable results.

A frequency-response analysis was performed to explore the expected relationship between the operator's internal plant model and certain aspects of the task environment: specifically, (1) the availability of rate and/or acceleration cues, and (2) the complexity of the plant dynamics. The qualitative results obtained in this analysis supported the following explanations for some of the data trends shown in this and previous studies:

1. The lower observation noise and motor time constant parameters found for whole-body motion cueing (Figure 1-5) are due to the more accurate internal plant model attainable in this cueing environment.
2. Learning is more rapid in a motion-base environment because the operator is more readily able to determine the correct order of the plant dynamics.
3. The apparent degradation in information-processing capabilities associated with high-order plants (Figure 1-3) is, in part, a reflection of a degraded internal model of the task environment.

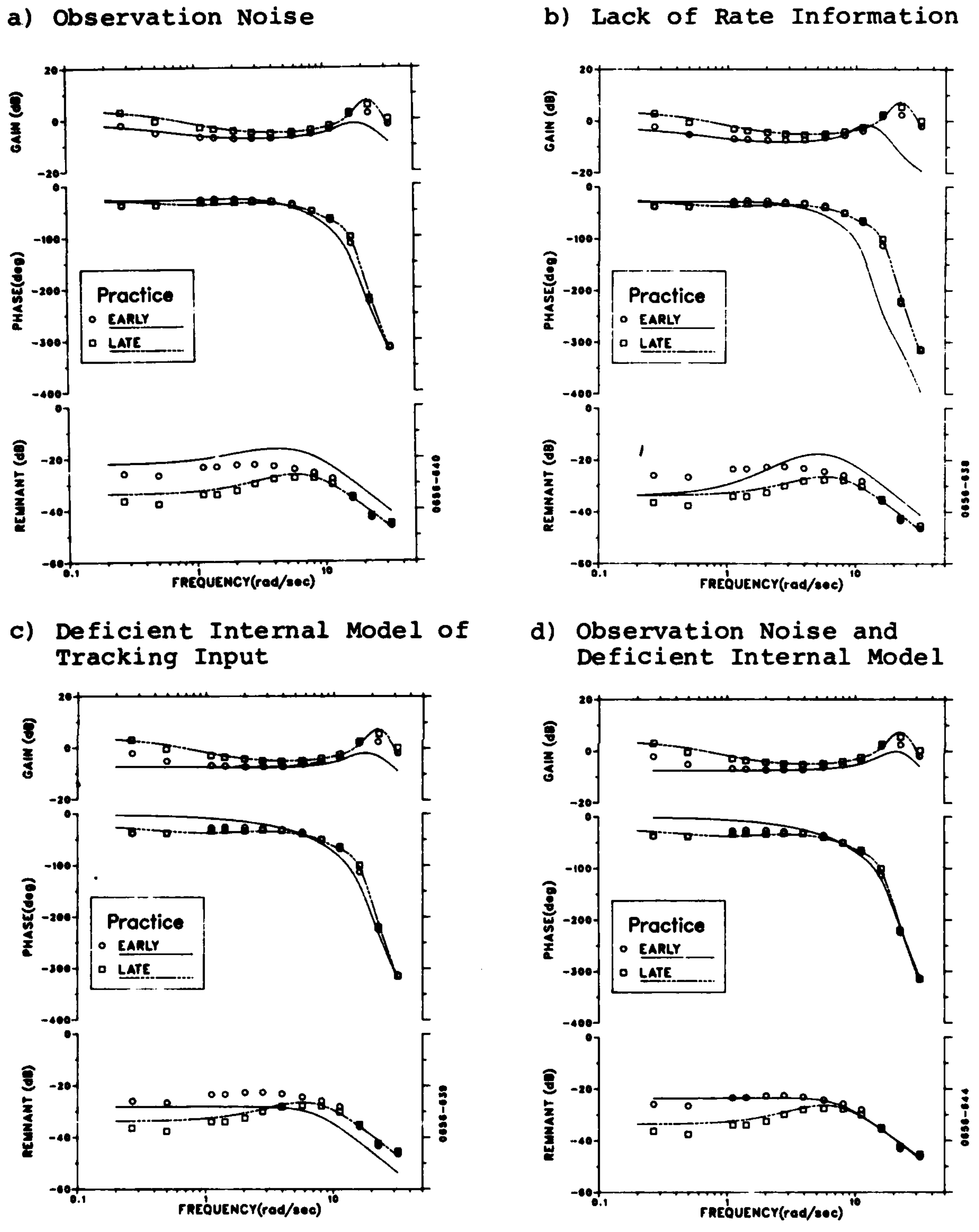



Figure 1-6. Results of Hypothesis Testing, Unstable-Plant Task

The results of this suggest that we consider modifying the OCM structure as shown in Figure 1-7. The structure is similar to that of the baseline model shown in Figure 1-1, with the addition of a fourth adaptive element -- the "optimal identifier". As the name implies, this model element would mimic the way in which the human operator identifies plant and input dynamics, and it would use this information to properly configure the remaining adaptive model elements. A considerable body of literature in the areas of identification theory and adaptive control theory could be drawn upon to aid such an undertaking. If properly formulated, the restructured OCM should be able to address issues not only of operator skill development, but also of performance difficulties (such as PIO's) that arise when substantial lags and delays are introduced into the system.

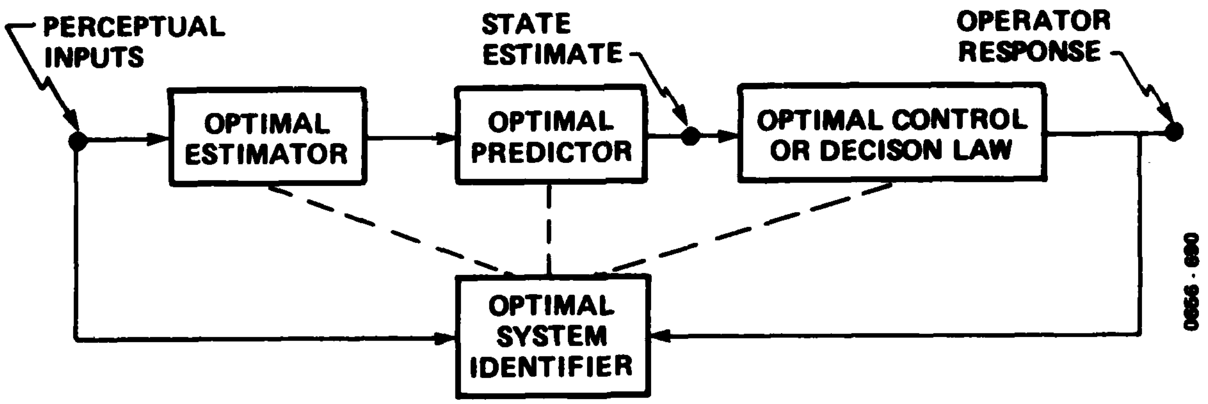



Figure 1-7. Proposed Structure for Model of Operator Response Strategy

# 2. BACKGROUND

Considerable effort has been devoted to understanding human learning phenomena, and to developing models for human performance in continuous control tasks, but very little work has been done in developing quantitative models for how the operator learns the appropriate control and estimation strategies. Furthermore, what work has been done does not lend itself readily to complex multi-input, multi-output tasks, nor does it extend to the kinds of monitoring and decision tasks associated with aircraft flight management.

This chapter provides the following background: (1) a review of some important concepts related to skill development; (2) a brief description of the optimal-control pilot model including techniques for identifying, from experimental data, model parameters associated with human information-processing limitations; and (3) a review of relevant experimental and analytical results, in which we demonstrate what appears to be an interaction between the parameters of the control task and the quality of the operator's internal model of the task environment.

## 2.1 Skill Acquisition

Before discussing general theories of human operator skill acquisition we must first consider some distinctions that enter into the assessment of skilled performance. Specifically, we consider the differences between (a) adaptation and learning, (b) performance and learning, and (c) level of skill attainable and rate of skill acquisition.

### 2.1.1 Concepts

*Adaptation vs. Learning*

If an automobile operator owns both a stick-shift and an automatic-shift vehicle, he is equally capable of operating either one and we say the operator adapts his behavior to the vehicle currently being operated. However, if the operator owns only an automatic shift vehicle and rents a manual shift vehicle, a period of learning is required to modify the pre-existing behaviors to meet the requirements of shift and clutch operation. Following this period of learning, the operator can call up the relevant behaviors on demand. Thus we define adaptation in this context as the calling up of previously-learned behaviors suitable to the circumstances and context of concern. Learning, on the other hand, is the acquisition of these desirable behaviors on the basis of practice or repeated experience.

Learning, rather than adaptation, is the focus of the work described in this report.

*Performance vs. Learning Effects*

Suppose we wish to evaluate the usefulness for learning of a new display or of the introduction of motion in the training simulator. We test two groups of pilots -- one with the old display (no motion), and one with the new (with motion). While we may observe improved performance in the test condition, we cannot conclude that greater learning has taken place without examining performance in a transfer condition that is representative of the conditions in which the learned skills must be used. The test condition may produce a performance effect but no learning. Similarly, a particular training condition may actually produce worse performance but contribute importantly to more effective performance upon transfer to the desired end conditions. Thus, only a carefully designed transfer experiment will distinguish between performance and learning effects.

*Attainable Skill vs. Rate of Skill Acquisition*

The effectiveness of training systems (with regard to skill development) can be evaluated in terms of (1) the asymptotic level of skill that can be acquired, given sufficient exposure to the task, and (2) the rate at which skill is acquired. Although one might expect that a training environment which maximizes the quality of overall system performance also maximizes learning rates, one cannot be guaranteed a positive correlation between learning rate and asymptotic skill level.

In summary, the interaction between informational cues, asymptotic skill level, and learning rate is an issue of practical importance, and is one that must be addressed by models that are developed to predict learning behavior.

### 2.1.2 Some Theories of Learning

The psychological literature is rife with theories of learning, many of which purport to apply to perceptual-motor skill learning. Few of these theories provide a suitable foundation for quantitative models for tasks related to flight management. Habit-strength theories fail to address what is actually learned, dealing only with the successive build up of performance quality (Halgart and Bower, 1966). Skinnerian or shaping theories suggest that improvement takes place in small, incremental units and depend on temporally associated rewards, but this can hardly be considered a descriptive theory. Stimulus-sampling or cue-selection theories in the S-R tradition have been developed to a quantitative level, and at least for verbal learning they attempt to predict more than just the shape of a learning curve; but in the skill context they are not specific with respect to the characteristics of skill that are acquired

(Restle and Greeno, 1970). Crossman (1959) came the closest when he suggested that the operator samples a set of "methods" for accomplishing a task and on the basis of some unspecified evaluation criterion -- such as efficiency or effort -- selects out those methods or strategies that are more successful and efficient. However, Crossman was attempting only to describe the characteristics of the learning curve and not specific characteristics of skill acquisition.

Some attempts have been made at developing empirical models for control-strategy learning in terms of practice-related changes in performance metrics. Pew and Rupp (1971) attempted to measure stages of progression in terms of the cross-over model. They found systematic differences in the changes in these parameters among children of different ages and, in an unpublished study, Pew and Thomas mapped the coordinate changes in gain and time delay as a function of practice and then introduced a time-sharing task to see whether decrements in performance could be described reasonably as regressions along the same path in the gain-time delay space. Although there were rather large individual differences in the acquisition map for different subjects, it seemed clear that performance decrements associated with time-sharing were not simply regressions along the same path.

Smiley, Reid, and Fraser (1978) measured operator describing functions of novice automobile drivers during various stages of practice on an instrumented car. They found practice-related changes in both amplitude ratio and phase shift, which they interpreted as changes in the way the drivers were using the lateral position cue for steering control.

A few theoretical models, largely qualitative, have been proposed for control-strategy development. Kelley (1968) has formulated an extensive theory of performance and skill acquisition

that builds on the basic concept that learning consists of the acquisition and refinement of an internal model that defines control strategy and relates it to his model of the environment in which the operator is controlling. This environment includes the characteristics of the controlled element as well as the initial conditions.

More recently, theories of skilled performance have introduced the concept of a schema (Pew, 1974; Schmidt, 1975 and 1976), a generalized standard of performance from which may be extracted a particular instance for execution as a motor program for any given set of initial conditions. The idea of a schema is largely compatible with the notion of a general form of internal model.

Expanding on the notions of schemata, Rumelhart and Norman (1976) propose three modes of learning: (1) the acquisition of new data, using existing schemata to organize the new information; (2) "tuning" the parameters of existing schemata to better fit the data; and (3) restructuring, whereby new schemata are developed when existing memory structures are inadequate to account for new knowledge. No mechanisms are proposed for effecting these changes, however.

Another conceptual framework for control-strategy development -- which incorporates some of the notions expressed above -- is the "Sensory Organization of Perception" proposed by McRuer and colleagues (Krendel and McRuer, 1960; McRuer and Jex, 1967). According to this theory, control-strategy development is assumed to undergo three stages: (1) development of "compensatory" skills, in which appropriate feedback laws are established for stabilization and control, (2) development of "pursuit" skills, in which sufficient knowledge is gained to allow application of a partial feedforward strategy, and (3) a "precognitive mode" in

which the pilot is able to take full advantage of any predictability inherent in the external inputs and can act in a generally "open-loop" fashion.

A more specific hypothesis has been proposed by Fuchs (1962) in which the operator is assumed to place increasing emphasis on velocity and acceleration cues as skill improves. Although this hypothesis has intuitive appeal, it is not well supported by Fuchs' own work, nor is it supported by the results presented later in this report.

A scheme for both modeling and assessing operator control behavior, implemented by Greene et al (1980), builds upon the notion of internal modeling and attempts to account for learning by building up a representation of plant dynamics through experience. "Knowledge" is represented by a matrix of learned relationships between tracking error and control response. While this model has been able to replicate human operator behavior in a pursuit tracking task using proportional dynamics, it would appear to suffer severely from the "curse of dimensionality" with respect to modeling multi-input, multi-output high-order systems.

## 2.2 The Optimal Control Model

The reader is assumed to be generally familiar with the optimal-control model (OCM) for pilot/vehicle systems. This model has been used in numerous studies performed for AFAMRL by BBN (Levison, Baron, and Junker, 1976; Levison and Junker, 1977, 1978; Levison and Zacharias, 1981). For the reader's convenience we first review the pilot-centered components of the model and then summarize the procedure for identifying independent (i.e., pilot-related) model parameters from experimental data.

### 2.2.1 Model Description

We consider two categories of pilot-related model elements: parameters that reflect the human's perceptual-motor (information-processing) limitations, and elements related to the operator's adaptive response strategy.

The following parameters reflect perceptual-motor limitations:

1. Observation noise. Each perceptual variable utilized by the operator is assumed to be perturbed by a white Gaussian noise process that is linearly uncorrelated with other pilot-related or external noise sources. In certain idealized laboratory tracking situations, the variance of the observation noise tends to scale with the variance of the corresponding display variable (Baron and Levison, 1980), in which case we may characterize this limitation by an observation noise/signal ratio. A more complex submodel for observation noise may be considered to account for limitations such as perceptual thresholds (Baron and Levison, 1975,1977) and attention-sharing (Levison, Elkind and Ward, 1971; Levison, 1979). In general, the observation noise accounts for most of the operator's "remnant" -- the portion of the control input that is not linearly correlated with external inputs. For trained subjects, remnant may reasonably be attributed to fundamental information-processing limitations as suggested above (provided the system to be controlled is linear -- an underlying assumption of the OCM). For untrained subjects, observation noise may reflect within-trial variations in the linear aspect of the operator's response strategy.

2. Time Delay. A single (scalar) time delay is added to each display variable to account for the various sources of delay associated with information acquisition, transformation, and response execution.

3. Motor Time Constant. The operator's control response is assumed to be smoothed by a filter that accounts for an operator bandwidth constraint. In the model, this constraint arises directly as a result of a penalty on control rate introduced into the performance criterion. This constraint may mimic actual physiological constraints of the neuromotor system, or it may reflect subjective limitations imposed by the operator. The time constant of this first-order filter is called the "motor time constant".

4. Motor Noise. Just as an observation noise is postulated to account for perceptual and central processing inadequacies, a motor noise is introduced to account for an inability to generate noise-free control actions. In many applications this noise level is insignificant in comparison to the observation noise, but where very precise control is important to the conditions being analyzed, motor noise can assume greater significance in the model. Early implementations of the model treated this noise as a disturbance added to the control response commanded by the operator. In current OCM usage, motor noise is generally added to commanded control rate in order to provide a better match to low-frequency response behavior to the pilot describing function at low frequencies (Levison, Baron, and Junker, 1976).

5. Cost Functions. Except for the cost weighting on control rate, which we relate to a motor time constant as discussed above, the coefficients of the quadratic performance index are generally considered as part of the task description, rather than as human operator limitations. Nevertheless, the operator can only minimize what he perceives to be the performance index. To the extent this perception differs from the "true" performance index (as defined by the experimenter), the

performance index must be considered as an operator-related parameter. One might expect such differences to occur early in training.

The adaptive portion of the operator's response is represented collectively by three elements of the human operator model: The Kalman estimator, optimal predictor, and optimal control law. The function of the Kalman estimator and predictor is to generate the best estimate of the current state of system variables, based on the noisy, delayed perceptual information available. It is assumed in these elements that the operator has both an internal model of the dynamics of the system being controlled, and a representation of the statistics of the disturbances driving the system.

Given the best estimate of the current system state, a set of control gains or weighting factors are assigned to the elements of the estimated state, in order to produce control actions that will minimize the defined performance criterion. As might be expected, the particular choice of the performance criterion determines the weighting factors, and thus the effective control law gains.

### 2.2.2 Identification of Pilot-Related Parameters

An automated gradient search scheme has been developed by Lancraft and Kleinman (1979), and subsequently modified by Levison (1981a, 1981b), to identify the pilot-related model parameters listed above. Parameter values are found that provide a least-squared error joint match to experimental variance, gain, phase, and remnant measurements. Identification is generally performed under the assumption that the test subject has the correct internal model of the task environment.

As currently implemented, the parameter identification scheme places no constraints (other than non-negativity) on the identified values. Now, if all independent model parameters are allowed to vary freely to obtain a best match to a given data set, all parameters will generally vary from one data set to the next. In order to interpret such results, we need some method for determining which parameter changes are "significant"; that is, which parameter changes are necessary to account for changes in operator response behavior due to learning or to some change in experimental conditions. Relative magnitudes of various parameter changes are not reliable indicators of significance: a large change in the value of a particular model parameter may simply reflect insensitivity of the scalar modeling error to the value of that parameter.

A cross-comparison method has been developed by Levison (1981a, 1981b) to provide a qualitative significance test on parameter differences obtained from modeling the results of two experimental conditions. This method employs a numeric, non-analytic sensitivity test as described below.

Assume that we wish to analyze two data sets, corresponding to, say, the "baseline" and "test" experimental conditions; specifically, we wish to determine whether or not different parameter values are required to match these data. The null hypothesis, then, is that a single set of parameter values yields a near-optimal match to the "baseline" and "test" data.

To test the null hypothesis, we first identify three sets of pilot parameters using the gradient search scheme: (1) the set that best matches the baseline data, (2) the set that best matches the test data, and (3) the set that provides the best

joint match to the baseline and test data. For convenience, we shall refer to the parameters identified in step 3 as the "average parameter set".

We next compute the following four matching errors:

J(B,B) = matching error obtained from baseline data, using parameters identified from baseline data (i.e., best match to baseline data).

J(B,A) = matching error obtained from baseline data, using average parameter set.

J(T,T) = best match to test data.

J(T,A) = matching error obtained from test data, using average parameter set.

Finally, we compute the following "matching error ratios": MER(B) = J(B,A)/J(B,B), MER(T) = J(T,A)/J(T,T) and, if we wish to reduce the results to a single number, the average of these two error ratios.

In a qualitative sense, the greater the matching error ratios, the more significant are the differences between the parameters identified for the baseline and test conditions. For example, if both matching error ratios are unity (the theoretical minimum), then the null hypothesis is supported: there exists a single set of parameters that provides an optimal match to both data sets. Any differences between the baseline and test parameter sets must be considered insignificant and can be attributed to imprecision of the identification procedure. Conversely, if one or both matching errors ratios are substantially greater than unity, one must reject the null hypothesis and consider the differences in model parameters to be "significant"; i.e., to represent true differences in operator response behavior.

Interpretation of significant task-related differences in pilot parameters is contingent upon assumptions concerning the operator's internal model of the task. If we can be assured that the internal model is correct, parameter differences may be justifiably related to specific changes in operator response capabilities. For example, both theoretical and experimental results have led to the association of the observation noise/signal ratio to attention-sharing penalties among concurrent multiple tasks (Levison, Elkind and Ward, 1971; Levison, 1979). Observation noise, as one might expect, has also been found to reflect visual resolution limitations in non-ideal display environments (Levison, 1971). Similarly, increased motor noise has been found to account, in part, for tracking performance degradation caused by whole-body, high-frequency vibration (Levison, 1978). In these studies, performed with subjects who were well-trained on wide-band (i.e., low-order) control systems, the assumption of a near-perfect internal model was reasonable.

If the subject's internal model differs substantially from a true characterization of the task environment, parameter changes identified by the above procedure may be misleading. For example, suppose a test subject changes his internal model from one test condition to the next, but maintains the same inherent response capabilities in terms of motor time constant, observation noise, etc. By modeling both sets of data with the assumption of an invariant (and correct) internal model, performance differences will, of necessity, be revealed as changes in one or more "pilot" parameters.

Now, we can expect certain situations in which the subject is not likely to have a near-perfect internal model; e.g., tasks

requiring control of high-order systems with limited informational cuing, and subjects in early stages of training. The OCM has accordingly been modified to account for various imperfections in the operator's internal model (Levison, Baron, and Junker, 1976; Baron and Berliner, 1977). A theory has not yet been developed, however, to predict the nature or extent of internal modeling imperfections.

## 2.3 Some Evidence for Imperfect Internal Modeling

Figure 2-1 shows that a fixed set of pilot-related model parameters can yield a good qualitative match to frequency response measures (pilot gain, phase, and remnant) for a significant range of laboratory tracking dynamics. (The match can be improved, of course, by "tuning" the parameters for each condition.)

If we consider a wider range of tasks, especially tasks employing dynamics of higher order and/or greater delay, we begin to see a degradation in certain "pilot parameters" with increasing task difficulty. As discussed later, these results may reflect limitations on the operator's ability to construct an accurate internal model of the task environment.

Manual tracking data obtained in previous studies were re-analyzed using the parameter identification scheme described above. The results of this analysis, some of which have been reported previously by Levison (1981b), are summarized here.

Four classes of model parameters were identified from the tracking data: observation noise/signal ratios, motor noise/signal ratios, time delay, and cost of control rate. Nomenclature and definitions for these parameters are as follows:

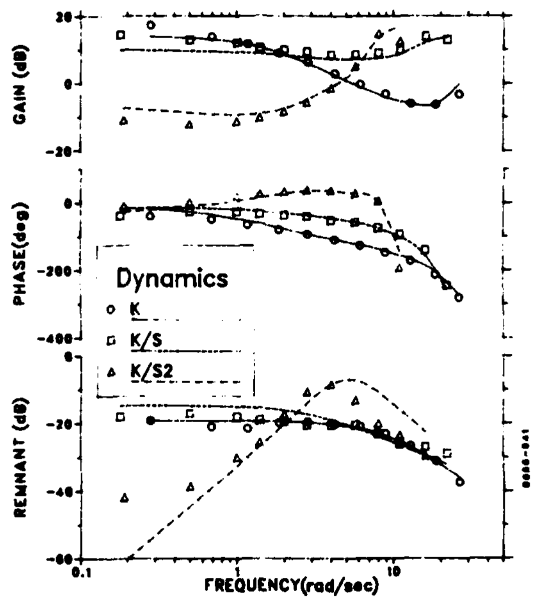



Figure 2-1. Fixed-Parameter Match to Three Tracking Tasks

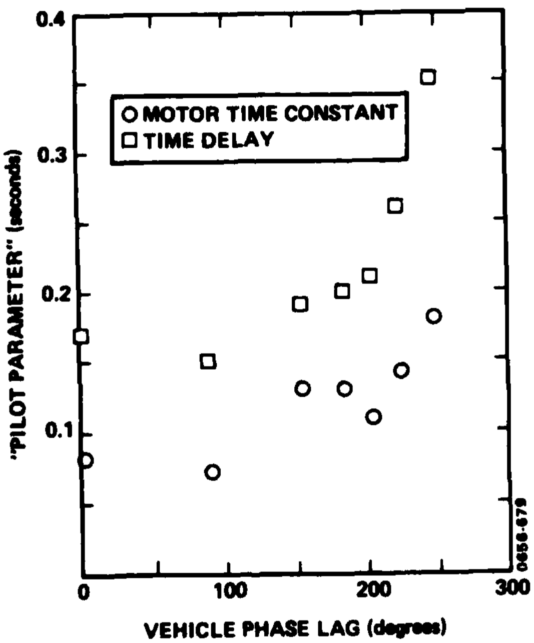



Figure 2-2. Effects of Task Difficulty on Independent Model Parameters

Pe = Observation noise/signal ratio relevant to tracking error, in dB. This quantity is defined as the ratio of the observation noise covariance associated with perception of tracking error, normalized with respect to tracking error variance. (Tracking error was a zero-mean process.)

$P\dot{e}$ = Observation noise/signal ratio relevant to perception of tracking error rate.

Pm = Pseudo-motor noise/signal ratio, in dB, defined as the ratio of pseudo motor noise covariance normalized with respect to the variance of the commanded control rate. The prefix "pseudo" signifies a noise process that only influences the pilot's response strategy; it does not reflect an actual noise process injected into the system. See Levison, Baron and Junker (1976) for a detailed discussion of the motor noise aspect of the OCM.

Td = Time delay, in seconds.

G = Cost coefficient associated with control-rate variance. (The operator is assumed to adopt a response strategy that minimizes a weighted sum of tracking error and control-rate variances.)

Tm = Motor time constant, in seconds. This parameter is not directly identified in the search procedure but is a derived parameter uniquely determined from the controlled-element dynamics and the identified G coefficient. Because this parameter is considerably less task-dependent than the weighting coefficient G, it is usually reported in place of G as a "pilot-related" parameter.

Parameter values for seven single-axis tracking tasks are shown in Table 2-1. The plant dynamics used in these experiments may be described as follows:

Configuration 1: Proportional control. (The pole at 200 rad/sec was introduced primarily to facilitate model analysis.)

Configuration 2: Rate control.

Configuration 3: Rate control plus a 2 rad/sec 2nd-order Butterworth filter.

Configuration 4: Rate control plus a 1 rad/sec 2nd-order Butterworth filter.

TABLE 2-1. PILOT-RELATED MODEL PARAMETERS, FIXED-BASE TRACKING, TRAINED SUBJECTS

| Config. Index | Plant Dynamics | Ref. | Pilot-Related Parameters Pe | Pė | Td | Tm | G |
|---|---|---|---|---|---|---|---|
| 1 | $K \cdot \frac{200}{s+200}$ | 1 | -21.0 | -19.5 | 0.17 | 0.082 | .40 |
| 2 | K/s | 2 | -23.6 | -18.2 | 0.15 | 0.073 | .0092 |
| 3* | $\frac{K}{s} \cdot \frac{2^2}{s^2+\sqrt{2}\cdot 2\cdot s + 2^2}$ | 2 | -18.5 | -17.6 | 0.26 | 0.14 | .0011 |
| 4* | $\frac{K}{s} \cdot \frac{1}{s^2+\sqrt{2}s + 1}$ | 2 | -22.4 | -13.3 | 0.35 | 0.18 | .0011 |
| 5 | $\frac{K}{s} \cdot \frac{5}{s+5} \cdot \frac{19}{s+19}$ | 3 | -22.1 | -16.6 | 0.19 | 0.13 | -- |
| 6 | $K/s^2 \cdot \frac{19}{s+19} \cdot e^{-.06s}$ | 4 | - 4.6 | -21.0 | 0.21 | 0.11 | .027 |
| 7** | (approximate 2nd-order) | 5 | -10 | -20 | 0.20 | 0.13 | -- |

Pe = displacement observation noise, dB

Pė = rate observation noise, dB

Td = time delay, seconds

Tm = motor time constant, seconds

G = relative cost of control rate, relating $(\text{lbs/sec})^2$ control rate to $(\text{arc-deg})^2$ error.

*Observation noise of about -19dB associated with perception error acceleration.

**Approximate pilot parameters determined from manual search.

References: (1) Levison (1981b); (2) Levison (1971); (3) Levison, Lancraft, and Junker (1979); (4) Levison (1980); (5) Levison, Baron, and Junker (1976)

Configuration 5: Approximate roll-axis fighter response characteristics including simulator lag.

Configuration 6: Acceleration control plus simulator lag and delay.

Configuration 7: High-order plant having approximate acceleration control in the mid frequency range.

The K, K/s, and $K/s^2$ conditions represented in Figure 2-1 correspond to configurations 1, 2, and 6, respectively.

The principal model results contained in Table 2-1 are presented graphically in Figure 2-2, where we see a trend toward larger motor time constant and larger time delay with increasing effective vehicle phase lag (computed at 4 rad/sec). For the most part, these task-related differences in model parameters are "significant" as defined above: they reflect differences in operator response behavior, rather than imprecisions in the identification procedure.

Now, since all subject populations were well trained, and since different groups of subjects tend to perform similarly on a given task when well trained, it is unlikely that these differences in pilot-related model parameters reflect different inherent information-processing capabilities among the experimental subject populations. Rather, the following hypotheses are more likely to explain the apparent trends:

1. Subjects were motivated differently by the different task configurations to perform to capacity.
2. Improper constraints have been imposed when applying the OCM to this data base, causing variations in what would otherwise be relatively invariant parameters.

Differences in observation noise (Table 2-1) can be attributed to motivational factors. For cases showing a large observation niose associated with error displacement, model analysis reveals that rms tracking error is substantially less sensitive to noise on error displacement than to noise on error rate. Conversely, the sensitivities are more nearly equal in cases where similar observation noises are identified for the two perceptual quantities. Thus, the observation noise trends are consistent with the hypothesis that the pilots are attempting, in part, to minimize perceptual workload by attending only as required to the available perceptual inputs (Levison, 1979).

Time delay differences, however, cannot be attributed to motivational factors. For example, adding a second-order 1 rad/sec Butterworth filter to K/s dynamics caused the best-fitting time delay parameter to increase from about 0.15 seconds (Configuration 2) to almost 0.35 seconds (Configuration 4). This difference was found to be significant using the qualitative test described above, and a sensitivity analysis showed that predicted tracking error variance was highly sensitive (about a factor of 2) to time-delay differences of this size. (See Section A.1, Appendix A).

These results indicate that (1) the subjects were capable of performing with a time delay parameter of under 0.2 seconds and (2), in the case where they exhibited a much larger delay, they would have been able to perceive the performance benefit of reducing the delay to 0.2 seconds or less. Therefore, we must consider the possibility that the larger delay reflects a limitation on operator performance not directly reflected in the model parameterization -- a limitation not present (or, at least, substantially less important) in the wider-band tracking tasks.

One hypothesis is that the accuracy and/or precision of the operator's internal model degrades as complexity of the controlled-element increases, and that this information-processing deficit is revealed (in the case cited here) as a change in time delay.

A number of hypotheses concerning the apparent task-related changes in the motor time constant were explored: (1) that the subjects select a motor time constant to reflect a consistent tradeoff between rms tracking error and rms control activity; (2) that the task-varying time constant reflects a consistent subjective performance penalty on the generation of control activity rather than a response bandwidth limitation, and (3) that the motor time constant reflects a response bandwidth limitation combined with a subjective penalty on control activity.

A sensitivity analysis reported by Levison (1981b) refutes the first hypothesis. The error/control tradeoffs identified for the various tasks varied over a wide range. Thus, we cannot relate differences in motor time constant to differences in the sensitivity of rms error to rms control rate.

Inspection of the right-hand column of Table 2-1 refutes the second hypothesis. Relative cost of control rate varies over two orders of magnitude among the various tasks for which meaningful comparisons can be drawn. Clearly, motor time constant is a more consistent descriptor of pilot performance limitations than is relative cost of control rate.

To test the third hypothesis of a combined bandwidth limitation and control-force penalty, we assumed the following submodel for the cost coefficient associated with control-rate variance:

$$G = G_o + G_p$$

where G is the actual coefficient, $G_o$ is the component that corresponds to some minimum motor time constant $Tm_o$ and $G_p$ is the component relating to the subjective penalty on physical activity (i.e., control-rate variances.) The assumed total performance index, or cost, was

$$J = \sigma_e^2 + G\sigma_{\dot{u}}^2$$

i.e., a weighted sum of error and control-rate variances.

Now, for the third hypothesis to be accepted, we need to find consistent (i.e., nearly invariant) values for $Tm_o$ and $G_p$ that replicate the task-related variation in $T_m$ shown in Table 2-1. The analysis reported in Section A.1 of the Appendix to this report yields mixed results. If we consider the data obtained from configurations 2, 3, and 4, we can find fixed values for $Tm_o$ and $G_p$ that yield motor time constants not significantly different from those shown in the Table. On the other hand, if we consider the database provided jointly by Configurations 2, 4, and 6, fixing $Tm_o$ and $G_p$ significantly degrades the model match, relative to the match that can be obtained if these parameters are allowed to vary across tasks.

It is possible that some alternative submodel structure would satisfactorily explain the variations in motor time constant (e.g., a penalty on control force instead of or in addition to, a penalty on rate-of-change of control force). An exhaustive search of such model structures was beyond the scope of this effort.

In conclusion, the analysis reported here is at least suggestive of the notion that task-related variations in identified "pilot parameters" of the OCM reflect some underlying limitation on human information-processing capabilities that

is not directly represented in the OCM as heretofore applied to tracking tasks. One obvious limitation to consider is the accuracy and precision of the operator's internal model. In Chapter 5 of this report we present a simplified analysis which supports the intuitive notion that the operator's internal model degrades as task complexity increases.

# 3. EFFECTS OF PRACTICE ON PILOT RESPONSE BEHAVIOR

In this section we review the effects of practice on manual control response behavior for three subject populations. Performance is quantified in terms of standard control-system performance metrics as well as "pilot-related" model parameters.

## 3.1 Review of the Data Base

The data base analyzed in this study was provided by two preceding experimental studies. The study referred to as the "stable plant" study was conducted primarily to explore the effects on pilot performance of a delay between roll-axis platform motion and visual cues (Levison, Lancraft and Junker, 1971), and employed simulated vehicle dynamics representative of a high-performance figher in roll. The study referred to as the "unstable plant" study was conducted as part of a research project to develop a tracking task for which performance would be highly sensitive to task- and environment-related stress (Zacharias and Levison, 1979), and employed plant dynamics having a divergence time constant of 0.5 seconds. The latter study was conducted fixed-base.

All subject populations were first given exposure to the tracking dynamics, without external disturbances, to allow subjects to develop an appropriate control strategy for stabilizing the plant dynamics. This initial exposure typically lasted a few minutes. A considerable period of practice followed, spread out over a number of days, in which the subjects attempted to minimize the effects of an external forcing function on mean-squared tracking error. The earliest data available for analysis of the type reported here, then, occurred early in the post-initialization phase; they do not represent the subjects' first exposure to the tracking dynamics.

The stable-plant tracking task consisted of maintaining a simulated figher-like aircraft wings level in the presence of random turbulence. Separate populations of 4-5 subjects were given initial training on the various conditions explored in this study. "Learning curves" are shown in Figure 3-1 for the subject populations trained (a) fixed base and (b) moving-base with synchronous visual and motion cueing. Averaged mean-squared tracking error is plotted as a function of practice session, where each session consisted of four experimental trials of approximately three minutes each.

Figure 3-1 shows that both the fixed- and moving-base subject populations improved their tracking performance scores with continued practice, with the latter subject group apparently reaching an asymptotic performance level during the course of training. The moving-base population not only achieved lower error scores than the fixed-base population, but exponential fits to the learning curves suggest that the moving-base population reached asymptote with fewer practice sessions (Levison, Lancraft and Junker).

The unstable-plant study required compensatory tracking using first-order unstable dynamics having a critical frequency of 2 rad/sec. The external disturbance consisted of a simulated first-order noise process injected in parallel with the subject's control input.

Each subject successfully completed 48 training runs. Because of initial difficulty with the task, subjects occasionally tracked an input disturbance RMS level of 0.5 cm, rather than the nominal 1.0 cm. To provide a fair base of comparison with scores obtained under nominal conditions, scores obtained with a 0.5 cm RMS input were doubled under the assumption of approximate operator linearity. A total of 24 such run scores were adjusted, out of a total number of 288 runs completed by the six-subject population.

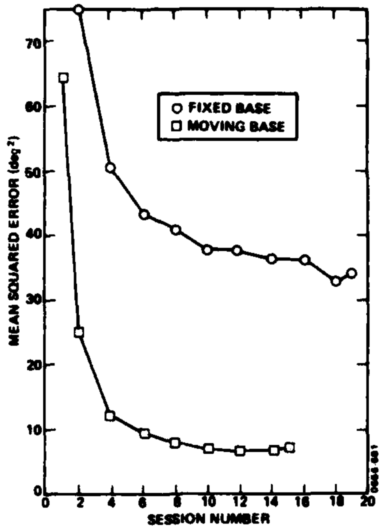



Figure 3-1. Effects of Practice on Mean-Squared Tracking Error, Stable Plant

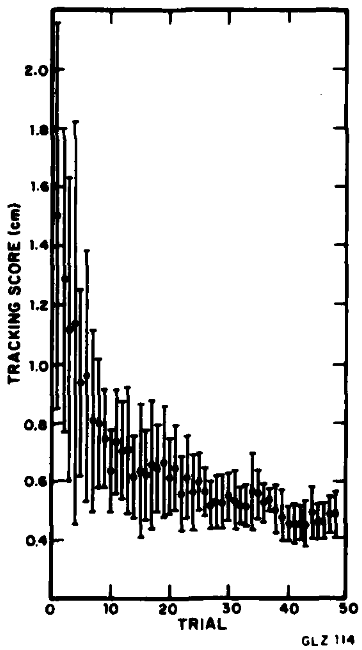



Figure 3-2. Effects of Practice on RMS Tracking Error, Unstable Plant

Figure 3-2 shows tracking score dependence on run number, averaged across the six subjects. Population means and standard deviations are indicated by the dots and bars, respectively. Although 48 runs per subject were conducted, the figure shows a substantial reduction in tracking score by about the 15th trial; by the 30th trial, tracking score was within 20% for the scores obtained at the end of training.

### 3.2 Effects of Practice on Operator Frequency Response

We present here a summary of the effects of practice on operator frequency response measures (gain and phase shift, and remnant). Data averaged across subjects are shown, along with selected data from individual subjects. Data for all subjects participating in the stable-plant and unstable-plant studies are presented individually in Appendix B.

The effects of practice on average frequency response are shown in Figure 3-3 for the three subject populations considered in this analysis: (a) stable plant, static group, (b) stable plant, motion group, and (c) unstable plant. Two stages of practice are reflected here and in the analysis to follow: very early in the training phase ("early"), and near-asymptotic performance at the conclusion of the training phase ("late"). In these figures (and in other frequency-response plots appearing in this report), 0 dB gain represents 1 unit of control response per unit of tracking error, and 0 dB "remnant" represents unit control variance per rad/sec for the portion of the operator's control response not linearly correlated with the external forcing function.*

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*For the stable-plant study, error was measured in degrees roll angle and control was in pounds force; for the unstable-plant study, error was in cm display deflection, and control was calibrated in terms of equivalent cm of steady-state error deflection.

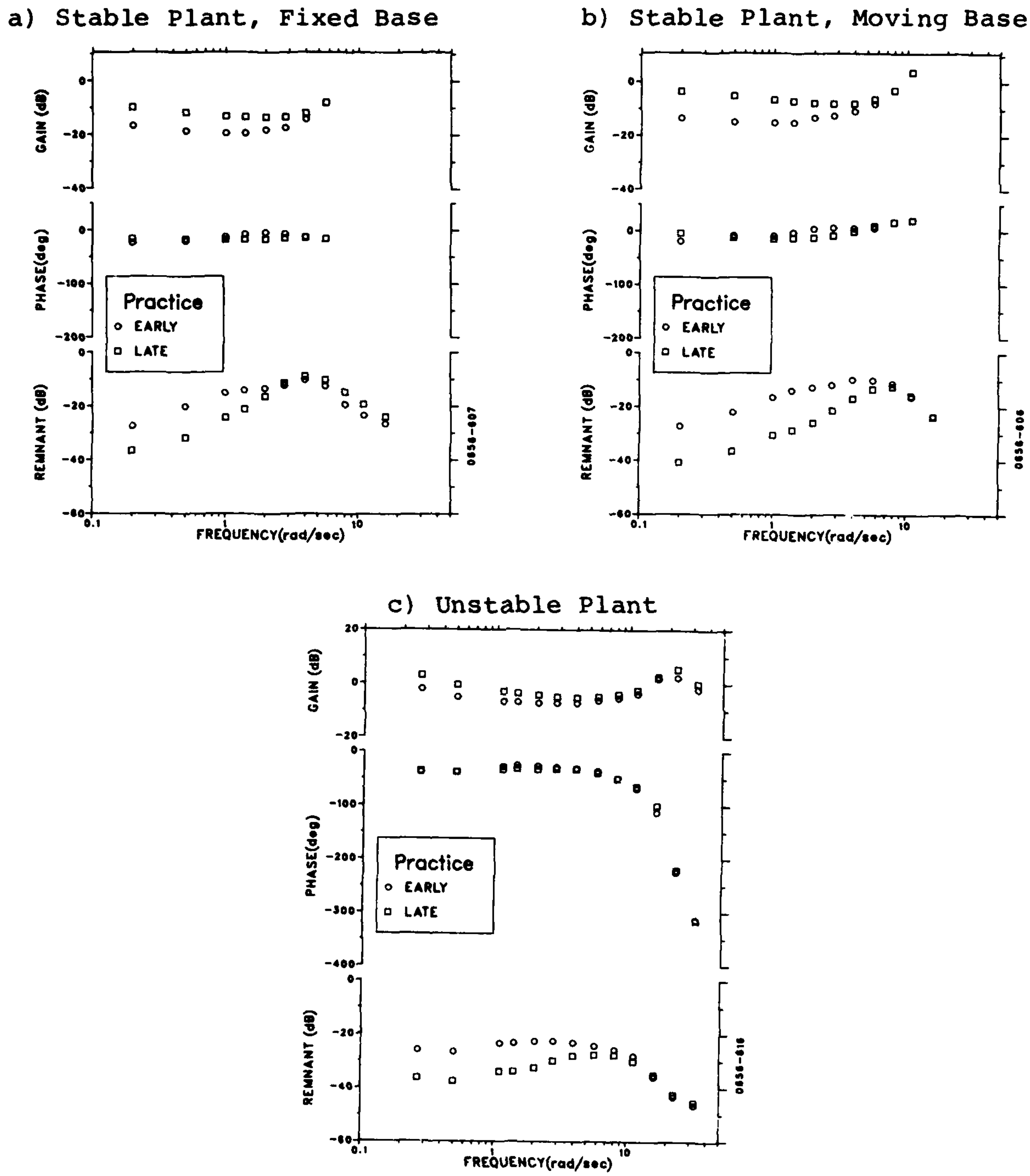


Figure 3-3. Effects of Practice on Average Pilot Frequency Response

Although the sum-of-sines forcing functions contained components ranging from about 0.2 to 32 rad/sec, signal/noise limitations due to operator remnant limited the range of valid describing function measurements. (See Levison, 1971, for a discussion of analysis procedures.) Thus, the range over which gain and phase measurements are plotted in Figure 3-3 are different for the different tracking tasks and different states of practice.

The three subject populations exhibited similar practice trends. Performance early in practice, relative to near-asymptotic performance, was characterized by lower pilot gain, minimal differences in phase shift, and higher remnant.

Five out of the six subjects participating in the unstable-plant study yielded frequency response measures very similar to the average response curves shown in Figure 3-3c. Thus, the average response may be considered typical of an individual subject's response, and model analysis of the population-average response is justified for that data base.

Intersubject differences in the practice trends were more substantial for the stable-plant study, and these results were analyzed on an individual as well as a group basis. Figure 3-4 compares frequency-response measures obtained from two subjects in the fixed-base group and two subjects in the moving-base group of the stable-plant study. In both cases, the subject pairs were selected to maximize intersubject differences.

The remnant spectrum showed the greatest variability with respect to practice effects. Two subjects in Figure 3-4 show that the remnant spectrum obtained early in practice was greater at low frequencies, and lower at high frequencies, than the corresponding remnant curves obtained later in the training phase. The remaining two subjects showed larger low-frequency remnant early in training, but negligible practice effects on high-frequency

a) Subject CP, Fixed Base

b) Subject DS, Fixed Base

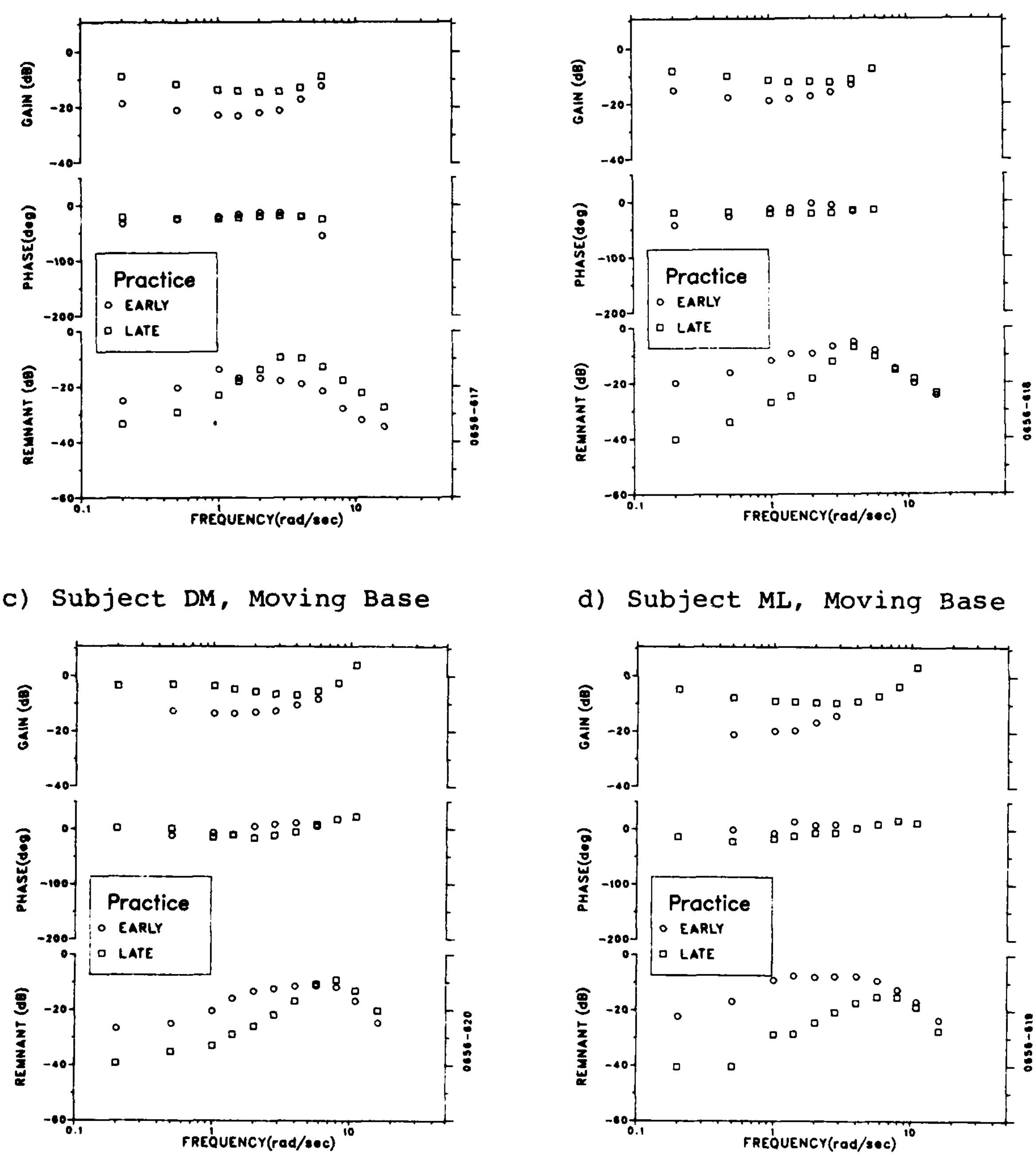


Figure 3-4. Practice Effects for Individual Subjects, Stable Plant

remnant. As discussed below, model analysis suggests that these different trends reflect differing practice-related effects on operator response bandwidth.

### 3.3 **Effects of Practice on Independent Model Parameters**

#### 3.3.1 Analysis procedures

The quasi-Newton gradient search procedure (Lancraft and Kleinman, 1979; Levison, 1981a,b) was used to identify the independent -- or "pilot-related" -- parameters of the OCM from data obtained early and late in the training phase. Parameters identified were the same as those defined in Section 2.3; in addition, a third observation noise/signal ratio $P_{\ddot{e}}$, associated with perception of error acceleration, was identified for the motion-base data.

Pilot parameters were identified for individual subjects in two ways. First, the full set of parameters was identified; this procedure is termed the "unconstrained" search procedure. Next, parameters were identified again with the following constraints placed on the search scheme: (a) time delay fixed at an appropriate value for all subjects, both practice conditions; (b) motor noise ratio fixed at the average value for early and late practice for a given subject, and (c) observation noise/signal ratios constrained to be the same for all observation noise parameters identified (e.g., $P_e = P_{\dot{e}}$ for a given subject at a given level of practice). This procedure, which is termed the "constrained" search procedure, considers only the overall observation noise/signal ratio and the motor time constant to be influenced by training.

The constrained search procedure is justified because, for the data base considered in this study, time delay, motor noise, and differences among observational noise variables were not significantly influenced by practice. (One should not conclude that these model parameters were redundant or nonidentifiable; rather, they were not indicators of the learning process.) As the reader will see, results are more readily digested if the search procedure is narrowed down to the important quantities.

Two techniques were employed to determine the significance of practice-related parameter differences: (1) the qualitative cross-comparison scheme described in Section 2.2.2, and (2) paired-difference t-tests performed on model parameters. Application of the t-test was the same as would be applied to the reduced tracking data, except that the identified parameters served as the "data". As a practical matter, this procedure was limited to analysis of population means, with subject-paired early/late differences used in the computation of the "t" statistic.*

### 3.3.2 Principle Results

Analysis of population trends is provided in this Section. Parameters identified for individual subjects are presented in Appendix B.

Table 3-1 shows the effects of practice on average pilot parameters for the static (fixed base) and motion (moving base) subject populations participating in the stable-plant study. The reader will notice invariant values for motor noise and time delay parameters for the "unconstrained" search performed for the motion population (lower half of Table 1a). This constraint was imposed after preliminary analysis with an unconstrained procedure indicated that (1) practice had no significant influence on these parameters, and (2) numerical convergence was substantially improved from this particular data set by imposition of these constraints.

The unconstrained and constrained search procedures revealed similar trends for practice-sensitive model parameters. Both observation noise and motor time constant decreased with practice for the two populations, with time constant differences being greater for the static group. Table 3-1a (static group) shows negligible changes in motor noise, an <u>increase</u> with practice in the time delay, and apparently greater practice effects on position-related noise as compared to rate-related noise. However, time

*Significance testing for individual subjects would require parameter identification for a number of individual trials per subject, which would generally entail significant computational requirements.

Table 3-1. Effects of Practice on Average Pilot Parameters, Stable-Plant Study

a) Unconstrained Parameter Search

| Motion Condition | Practice State | Statistic | Parameter | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | Pe | $\dot{\mathrm{Pe}}$ | $\ddot{\mathrm{Pe}}$ | Pm | Td | Tm |
| STATIC | EARLY | MEAN | -10.5 | -15.6 | - | -41.9 | .187 | .205 |
| | | SD | 3.1 | 1.9 | - | 11.1 | .032 | .084 |
| | LATE | MEAN | -22.5 | -18.7 | - | -40.6 | .221 | .135 |
| | | SD | 2.1 | 2.3 | - | 10.1 | .044 | .021 |
| MOTION | EARLY | MEAN | -13.4 | -14.1 | -19.5 | -60.0 | .200 | .121 |
| | | SD | 8.1 | 2.4 | 2.6 | - | - | .015 |
| | LATE | MEAN | -32.4 | -13.7 | -24.9 | -60.0 | .200 | .0995 |
| | | SD | 1.2 | 6.3 | 4.4 | - | - | .0222 |

b) Constrained Parameter Search

| Motion Condition | Practice State | Statistic | PARAMETER | |
|---|---|---|---|---|
| | | | $\mathrm{Pe} = \dot{\mathrm{Pe}}$ | Tm |
| STATIC | EARLY | MEAN | -15.2 | .204 |
| | | SD | 1.4 | .083 |
| | LATE | MEAN | -18.9 | .135 |
| | | SD | 1.0 | .022 |
| MOTION | EARLY | MEAN | -15.4 | .124 |
| | | SD | 3.4 | .015 |
| | LATE | MEAN | -24.1 | .0994 |
| | | SD | 0.5 | .0222 |

Statistics for 5 subjects, static; 4 subjects, motion; 2-4 trials/subject

delay changes and differences between position and rate noise were found to be largely insignificant, thereby justifying the constrained search reflected in Table 3-1b. (The effects of imposing these constraints on the matching error are tabulated in Appendix B.)

Results of the significance test of practice-related parameter differences are given in Table 3-2. The t-tests indicated that only observation noise differences are significantly influenced by practice; this was true for both the static and motion groups. The qualitative cross-comparison test confirmed this conclusion for the motion group. For the static group, however, changes in motor time constant, but not observation noise, were found to be significant.

The discrepant conclusions yielded by the two significance testing methods may be due, in part, to appreciable subject-to-subject differences. Figure 3-5, which shows parameters identified for individual subjects, reveals an apparent negative correlation between practice-related effects on observation noise and motor time constant for the static group. That is, subjects exhibiting relatively large changes in motor time constant tended to exhibit relatively small changes in observation noise, and vice versa. This finding suggests some sort of tradeoff between decrements in motor time constant and decrements in observation noise in the early stages of practice. Because the parameter differences shown in Figure 3-5 were found to be largely significant (i.e., matching error ratio greater than 2), this presumed tradeoff does not simply reflect an insensitivity of the model-matching scheme. It is possible that performance was, to some extent, insensitive to piloting strategy early in training, with a consequent increase in inter-subject variability.

Table 3-2 . Significance Test of Practice-Related Parameter Differences, Stable-Plant Study

| Motion Condition | Search Procedure | Test Procedure | Parameter Pe | Pė | Pë | Pm | Td | Tm |
|---|---|---|---|---|---|---|---|---|
| STATIC | Unconstrained | t-test | * | - | N/A | - | - | - |
| | Constrained | t-test | * | | N/A | N/A | N/A | - |
| | Constrained | Qualitative | - | | N/A | N/A | N/A | * |
| MOTION | Unconstrained | t-test | - | - | * | - | - | - |
| | Constrained | t-test | * | | | N/A | N/A | - |
| | Constrained | Qualitative | * | | | N/A | N/A | - |

N/A = not applicable

\- = not significant

* = alpha significance level 0.05 or less for the t-test, matching error ratio greater than 2.0 for the qualitative test.

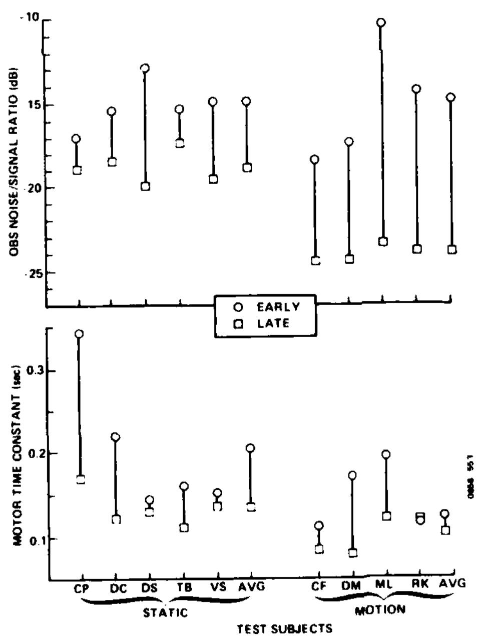


Figure 3-5. Effects of Practice on Pilot-Related Model Parameters, Stable-Plant Study

Results of the model analysis were more consistent for the unstable-plant study. Table 3-3 shows that practice influenced primarily the observation noise/signal ratio for the subjects participating in this study. Both methods for determining significance indicated that only the noise parameters were significantly effected. On the average, motor time constants and observation noise/signal ratios were lower than those obtained in the motion-cue study, perhaps because of the more severe information-processing requirements imposed by the unstable plant dynamics used in the unstable plant study.

Table 3-3. Effects of Practice-Related Model Parameters, Unstable-Plant Study

a) Model Parameters

| Practicing State | Statistic | Parameter | | | | |
|---|---|---|---|---|---|---|
| | | Pe | Pė | Pm | Td | Tm |
| EARLY | MEAN<br>SD | -18.0<br>2.3 | -20.0<br>2.4 | -44.2<br>9.3 | .141<br>.032 | .105<br>.029 |
| LATE | MEAN<br>SD | -24.2<br>1.4 | -22.2<br>0.7 | -42.2<br>7.3 | .135<br>.013 | .0809<br>.0145 |
| EARLY | MEAN* | -19.5 | | -45.0 | .135 | .0863 |
| LATE | MEAN* | -22.4 | | | | .0786 |

*Search performed under following constraints:
PYe = PYė, Pm = 045, Te = .135.

Statistics for 6 subjects, 2-4 trials/subject.

b) Significance Tests

| Analysis Procedures | Parameter | | | | |
|---|---|---|---|---|---|
| | Pe | Pė | Pm | Td | Tm |
| Unconstrained search, t-test | * | - | - | - | - |
| Constrained search, qualitative test | * | | N/A | N/A | - |

N/A = not applicable

- = not significant

* = alpha significance level .05 or less for the t-test, matching error ratio greater than 2.0 for the qualitative test.

Statistics for 6 subjects, 2-4 trials/subject

# 4. HYPOTHESIS TESTING

The model results presented in the previous section were obtained without imposing pre-conceived notions as to what the effects of practice might be. All pilot-related independent model parameters were initially allowed to vary at will across conditions; only after determining that certain parameters were insensitive to practice effects were constraints subsequently imposed on the search procedure. In this initial analysis phase, then, the OCM was used strictly as a diagnostic tool. As the next step toward developing a predictive model for learning, the data base was re-analyzed, this time with constraints imposed to reflect various hypotheses concerning the process of skill acquisition. The goal of this second analysis phase was to characterize learning effects in a manner that was parsimonious and yet applicable to a predictive model for learning.

We explore here various hypotheses concerning information-processing deficits early in the training phase, relative to information-processing capabilities after substantial practice. Some of these hypotheses are suggested by the results presented in the preceding chapter, others by existing theories of learning. Potential deficits are first explored individually, then in combination. All model/data comparisons are with respect to frequency-response data/averaged across subjects within a given population (5 subjects for the static group, stable-plant study; 4 subjects for the motion group, stable-plant study/ and 6 subjects for the unstable-plant study).

One should keep in mind that the "early" practice data reflect operator performance only after the operator has learned to stabilize the plant and is able to track for a three- to four-minute period. Therefore, performance early in training does not

necessarily reflect operator capabilities and strategies upon first exposure to the tracking task. Although steady-state data were generally obtainable after relatively brief exposures to the task, one must consider the possibility that a substantial amount of learning (especially regarding plant dynamics) occurred between first exposure and the "early" practice results reported here.

## 4.1 Increase in the Observation Noise/Signal Ratio

The analysis reported in the previous chapter suggests that observation noise differences should account for much of the practice effects. The following test was therefore performed: (1) independent model parameters were initially set to the values identified by the constrained-search procedure from the late-practice data, and (2) the observation noise/signal ratio was increased until the early-practice average MSE score was matched to within 10%. A fixed noise/signal ratio was maintained for the position and rate components, and all other parameters were kept fixed at the values appropriate for late practice. The objective of this analysis, then, was to determine how well practice effects could be accounted for by a change in a single model parameter; specifically, observation noise/signal ratio.

The effects of changing the observation noise are shown in Figure 4-1. In order that one may qualitatively judge the accuracy of the model trends, average frequency-response experimental data are shown for comparison.

As the reader will shortly see, this hypothesis provides the best simple explanation for observed performance trends. For all three tracking tasks, predicted gain is decreased and predicted remnant is increased.* Not all details of the early/late

*Throughout this discussion, a comparison of early-practice behavior to late-practice behavior is implied.

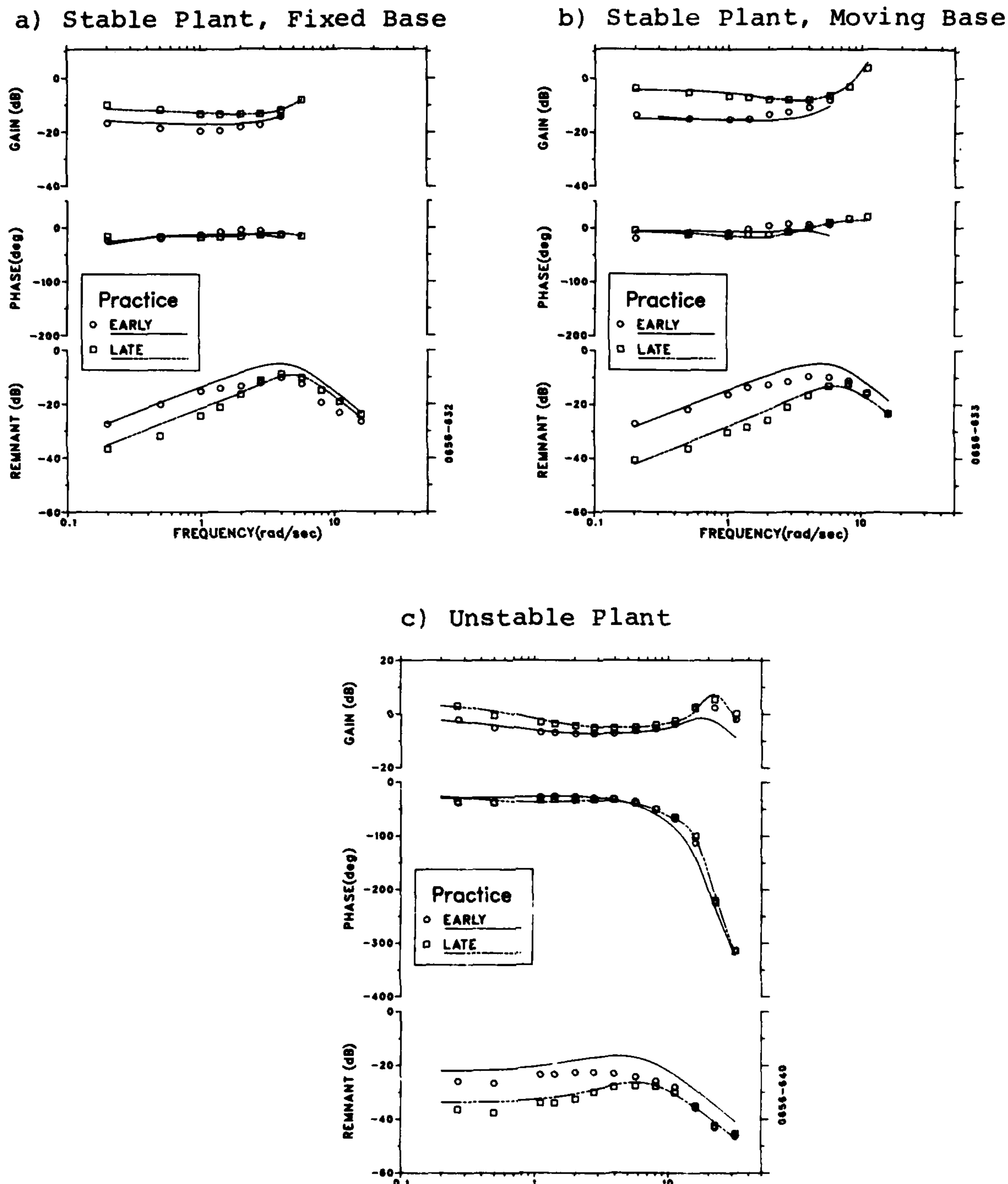


Figure 4-1. Effects of Increased Observation Noise/Signal Ratio

differences are modeled, however. In particular, the model predicts that remnant will be increased at all measurement frequencies; the experimental data show that high-frequency remnant was either unmodified or slightly decreased. Furthermore, Figure 4-1c shows a greater effect on the high-frequency gain peak than was observed. (Valid high-frequency describing function estimates were not obtained for the stable-plant tracking tasks.) There also seems to be a tendency for predicting too much phase lag at mid-to-high frequencies.

## 4.2 Lack of Information on Error Derivatives

It has been suggested that an untrained operator makes relatively little use of rate information provided by the velocity of the error indicator, and that the reliance on this type of information increases with continued practice (Fuchs, 1962). To test the validity of this hypothesis, model parameters were initially selected as in the previous test, and the "display vector" was reduced to a single quantity: error displacement. Thus, rate cues were eliminated from the analysis of the fixed-base tasks, and both rate and acceleration cues were omitted from the analysis of the moving-base task.

Figure 4-2 shows that this hypothesis produces some predicted performance trends that are counter to experimental observations. Although the effects of practice on low-frequency gain are matched reasonably well, too much high-frequency phase lag is predicted, and the predicted remnant trends are wrong. Specifically, this hypothesis predicts that remnant will be increased largely at high frequencies, whereas the data show the increase to be primarily at low frequencies. Thus, the hypothesis of a specific deficiency in extracting and utilizing velocity information early in practice is not supported.

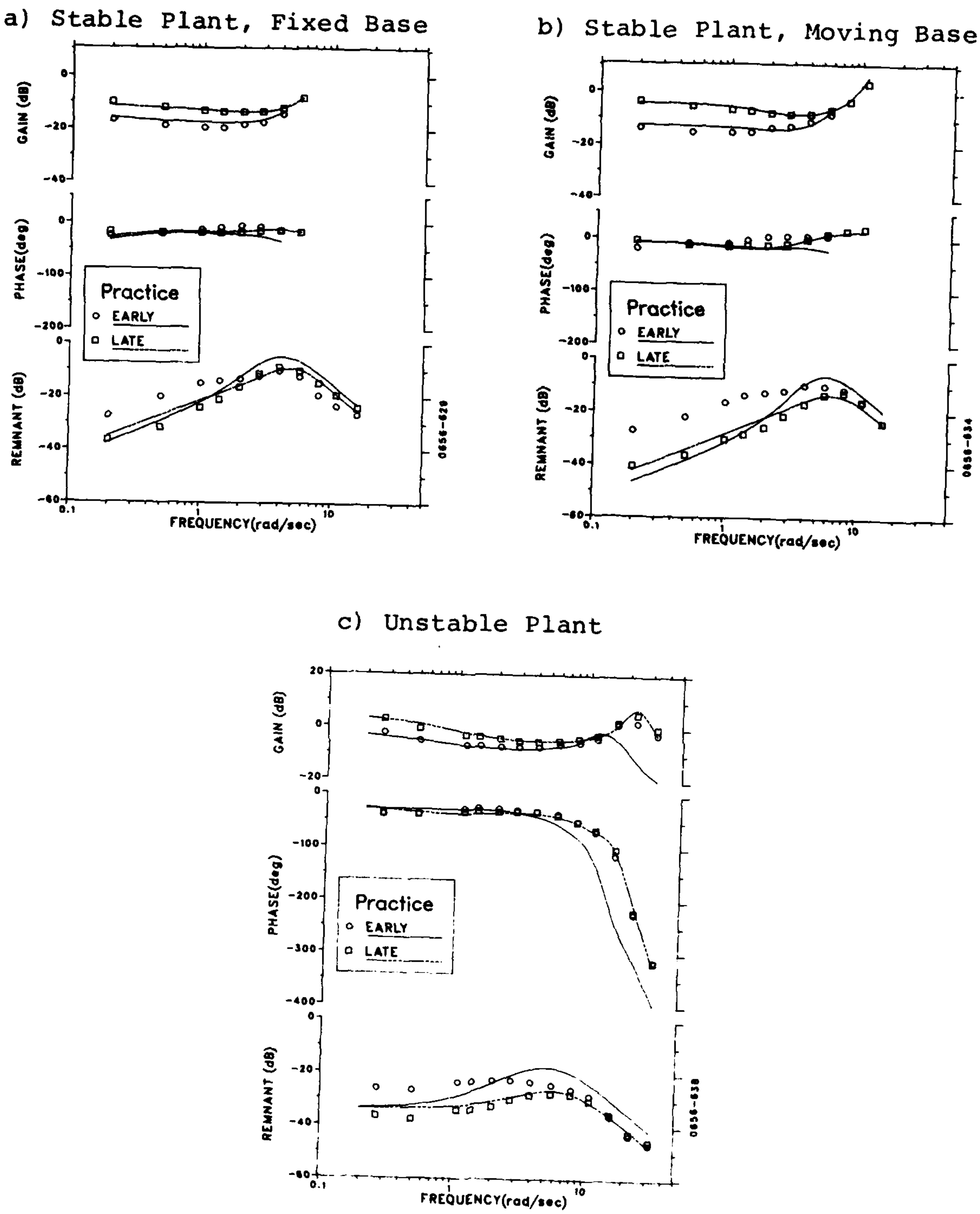


Figure 4-2. Effects of Lack of Information on Error Derivative

### 4.3 Deficient Internal Model of the Tracking Input

As noted above, the "early" results presented here do not represent the subjects' first exposure to the tracking tasks, but rather the first available opportunity to obtain consistent performance measures once the subjects have learned some rudimentary strategy for stabilizing and controlling the vehicle. Consequently, it is possible that a substantial portion of the learning taking place during the practice intervals relevant to these data bases was devoted to learning the statistics of the external inputs. This hypothesis is consistent with the "Sensory Organization of Perception" theory (Krendel and McRuer, 1960; McRuer and Jex, 1967), in which control-strategy development is assumed to undergo three stages: (1) development of "compensatory" skills, in which appropriate feedback laws are established for stabilization and control; (2) development of "pursuit" skills, in which sufficient knowledge is gained to allow application of a partial feedforward strategy; and (3) a "precognitive" mode in which full advantage is taken of any predictability of the external inputs.

In keeping with these notions, a third hypothesis was tested; namely, that performance deficiencies early in practice can be accounted for by a deficient internal model of the input statistics. To test this hypothesis, the (mathematical) "pilot" was assumed to have no knowledge of the correlations inherent in the forcing function. A white-noise (internal) model of the input was assumed, and the covariance of this white noise was adjusted to match early-practice MSE scores, with other pilot-related parameters fixed at values appropriate for asymptotic tracking.

Figure 4-3 shows that practice effects on pilot gain are matched over much of the spectrum. However, low-frequency phase effects (not seen in the data) are predicted, and the predicted remnant spectrum is uniformly too low. Thus, the notion of a

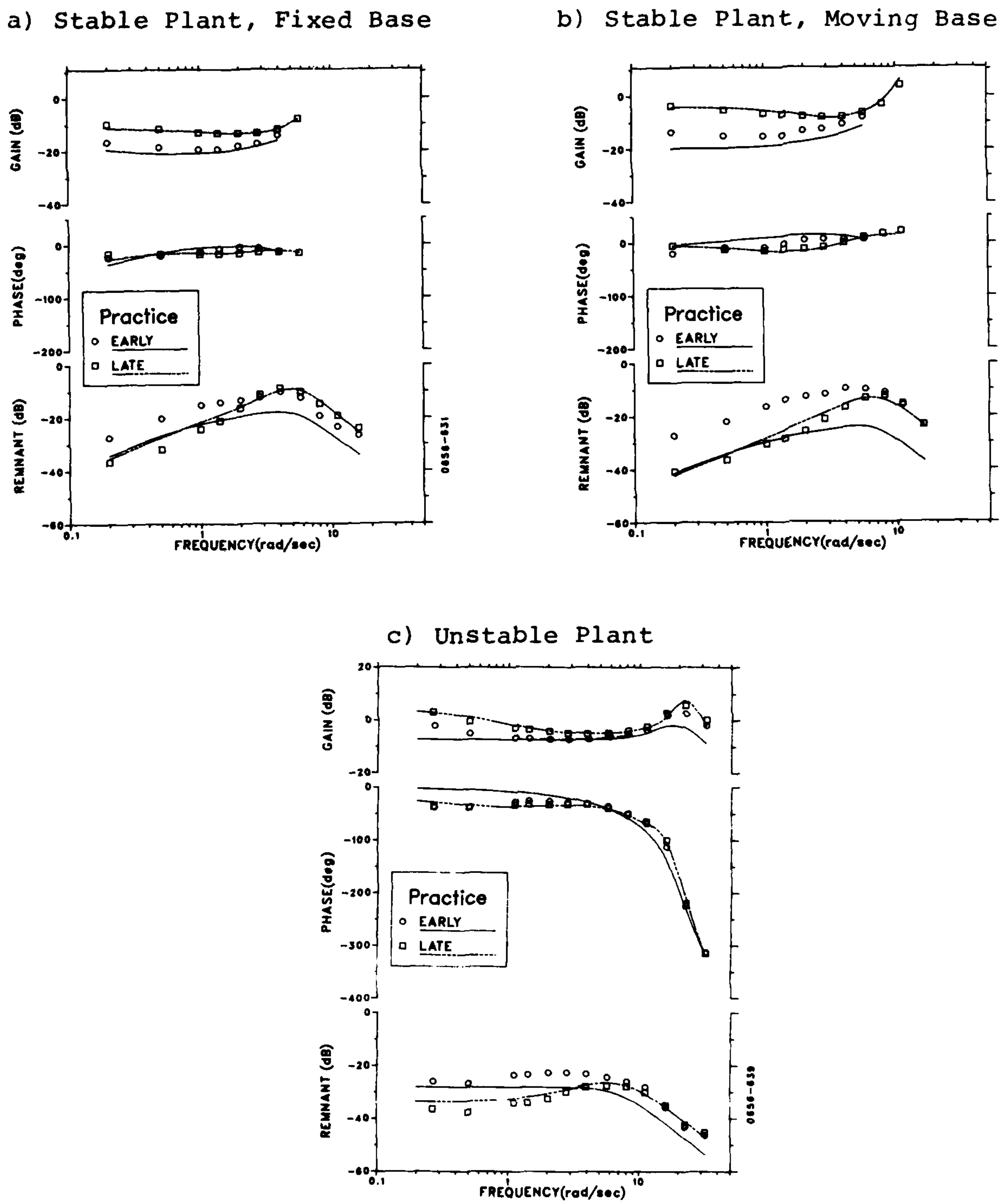


Figure 4-3. Effects of Deficient Internal Model of the Tracking Input

deficient internal representation of the tracking input is not sufficient as a stand-alone hypothesis to account for practice effects.

While it is reasonable to expect that the subject's internal model of the plant was also being refined during practice, model analysis was restricted to consideration of input modeling for two reasons. First, because of the mathematics involved, consideration of certain types of input-model deficiencies can be treated with considerably less computational cost than plant-model deficiencies. Second, the plant can be stabilized with a grossly deficient input model, and one has a rationale for choosing such a deficient model (e.g., the untrained subject is unaware of correlations within the input signal). On the other hand, severely deficient plant models cannot be explored because of resulting closed-loop instabilities, and there is no correspondingly obvious candidate for a plant model deficiency.

### 4.4 Combination of Observation Noise and Deficient Input Model

The foregoing results suggested a test of the combined hypothesis of increased observation noise and a deficient input model early in training. A gradient search was performed jointly on the internal white-noise input covariance, and the observation noise/signal ratio, to provide the best overall match to the early-practice data. Remaining parameters were fixed at values appropriate to asymptotic performance. Figure 4-4 shows that, on balance, a good match to the early data was achieved with this hypothesis.

### 4.5 Summary of the Hypothesis-Testing Exercise

The second analysis phase was begun with essentially a two-parameter match to practice effects (observation noise/signal ratio

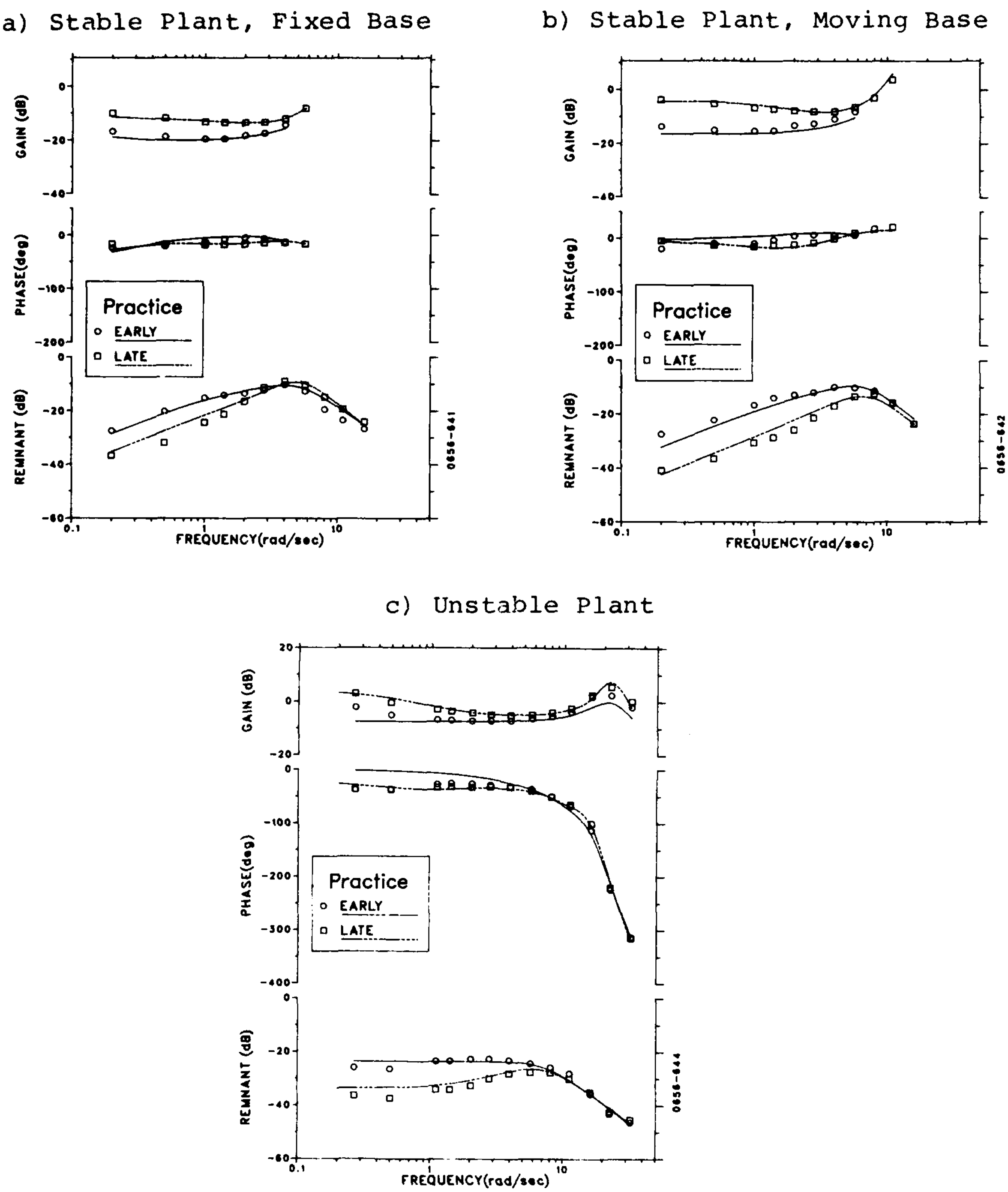


Figure 4-4. Effects of Increased Observation Noise Combined with Deficient Internal Model

and motor time constant), and it concluded with a different two-parameter match (observation noise/signal ratio and a deficient internal model).* Since either treatment is able to provide an acceptable data match, the decision concerning further model development must be guided by the remaining criteria proposed in the introduction; namely, one should pursue an approach that makes sense in terms of psychomotor capabilities and is most likely to lead to a model of predictive value.

Practice-related reduction in observation noise makes intuitive sense. Since observation noise is the mathematical device by which most of the pilot's "remnant" is accounted for, time variations and nonlinearities are reflected in the observation noise. One would expect that continued practice would bring about a more linear and stable response strategy.

One might also expect continued practice to enhance the operator's overall motor capability, which might well be reflected as a practice-related reduction in the motor time constant. However, as discussed in Chapter 2, extensive analysis of the data base suggests that the apparent changes in motor time constant are more directly related to the perceptual environment than to direct "motor training". For example, the subject population trained on the moving-base, stable-plant task had a lower average motor time constant early in practice than the fixed-base population had late in training. Since the subject populations were matched for tracking ability prior to the study, it is not likely that the apparent differences in motor time constants reflected inherent differences in response bandwidth capabilities. On balance, the evidence suggests that practice- and plant-related motor time constant represent differences in "perceptual efficiency" due perhaps to differences in the quality of the operator's internal model.

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*That is, variations in only two parameters are required to account for early/late performance differences. To match performance in a specific condition, non-zero values are typically associated with at least four "pilot-related" parameters, given the current model structure.

If we accept the notion that the subject's internal model changes with practice, we should be prepared to consider changes in the internal model of the plant as well as of the input. Furthermore, subsequent model development should address the problem of predicting how the internal model (and the observation noise/signal ratio) changes with practice, and how these practice effects are modified by the details of the task environment. These issues are addressed in a preliminary manner in the following chapter.

## 5. INTERNAL MODEL DEVELOPMENT: A PRELIMINARY TREATMENT

The practice effects explored in the preceding two chapters, along with some earlier results with high-order control systems, suggest that development of the operator's internal model of the control system is an important aspect of the "learning" that takes place in control (and presumably monitoring and decision) tasks.

One way of treating internal model development is to add a fourth adaptive element -- the "optimal identifier" -- to the OCM model structure as indicated in Figure 5-1. As the name implies, this model element would mimic the way in which the human operator identifies plant and input dynamics, and it would use this information to properly configure the remaining adaptive model elements.

Because of limited resources, a highly simplified model analysis was performed: one not in keeping with the framework of the OCM, but yet sufficient to allow a feasibility test. A two-operator task was considered, in which a "pilot" performed the roll-axis tracking task used in the stable-plant study referenced above, and an independent "observer" attempted to identify the plant dynamics. The observer performed this identification on the basis of the pilot's control input and the tracking error, and was prevented from making a perfect identification because of the effects of the tracking input (not directly available to the observer). The observer performed the identification by adjusting the parameters of a fixed-form model to reduce the mean-squared difference between "predicted" and observed tracking error.

A signal flow diagram of the hypothesized measurement situation is shown in Figure 5-2. All signals and system elements in this diagram are Laplace-transformed variables.

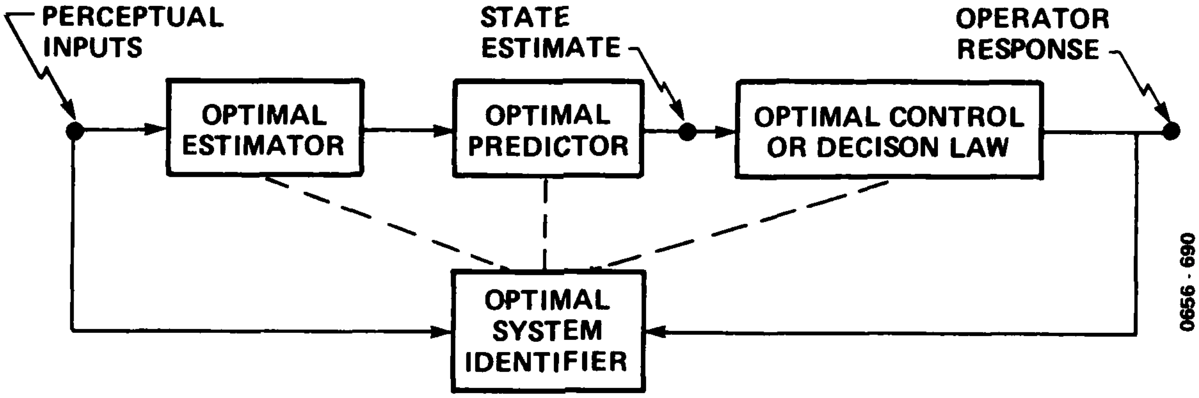
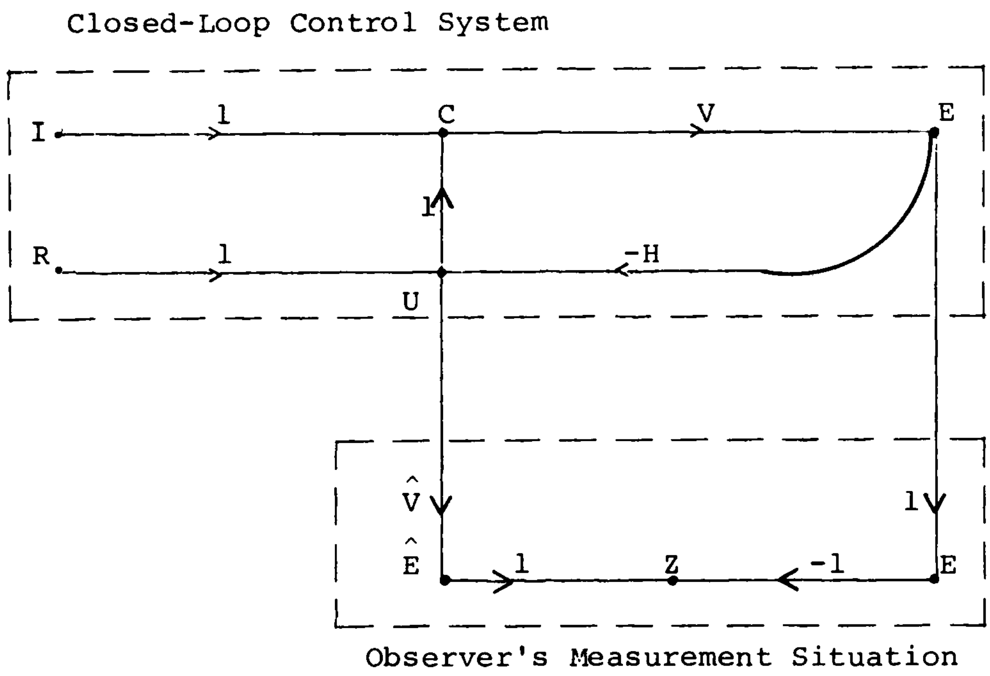



Figure 5-1. Proposed Structure for Model of Operator Response Strategy




I = Input Forcing Function

C = Total Input to Vehicle

E = Tracking Error

$\hat{E}$ = Predicted Tracking Error

R = Pilot Remnant

U = Pilot's Control Input

Z = Estimation Error

H = Pilot's Describing Function

V = Vehicle Dynamics

$\hat{V}$ = Estimated Vehicle Dynamics

Figure 5-2. Flow Diagram of Hypothesized Identification Task

The closed-loop tracking task is represented by the upper dotted box. The human operator ("pilot") H responds to tracking error E by generating a control input U. This control input is corrupted by an uncorrelated noise component, or remnant, R. The control signal is added with the disturbance input I to form the total input C to the controlled-element ("vehicle") V.

The observer (represented by the lower dotted box) is assumed to have perfect sensing of the tracking error and the operator's total control input (i.e., the sum of the input-correlated and remnant-related control actions). The observer is assumed to generate a model, or estimate, of the vehicle $\hat{V}$, which yields a predicted tracking error $\hat{E}$ when excited by the pilot's control input. The observer adjusts the estimated vehicle dynamics to yield minimum mean-squared estimation error Z.

The following spectral quantities are computed from Figure 5-2:

$$\Phi_{e_i e_i} = \frac{|V|^2 \; \Phi_{ii}}{1 + HV^{\,2}} \tag{5-1}$$

$$\Phi_{u_r u_r} = \frac{\Phi_{rr}}{|1 + HV|^2} \tag{5-2}$$

$$\Phi_{ZZ} = \frac{|1+H\hat{V}|\,|V|^2 \Phi_{ii} + |V-\hat{V}|^2 \Phi_{rr}}{|1 + HV|^2} \tag{5-3}$$

where subscripts "i" and "r" represent input-correlated and remnant-related signal components. Making use of the relationships expressed in Equations 5-1 and 5-2, we write Equation 5-3 as

$$\Phi_{ZZ} = |1-HV|^2 \; \Phi_{e_i e_i} + |V-\hat{V}|^2 \; \Phi_{u_r u_r} \tag{5-4}$$

The vehicle dynamics "identified" by the observer is the $\hat{V}$ that minimizes mean-squared Z, and the spectrum of this minimal Z is taken as the estimate of the tracking input. That is,

$$\Phi_{ii} = \Phi_{ZZ} \tag{5-5}$$

The above analysis is predicated on the assumption that the observer adjusts his model to minimize the difference between the predicted and actual tracking error. Alternatively, the model may be adjusted to minimize the prediction error for any derivative (or combination of derivatives) of the tracking error. In the case of the nth derivative, the model $\hat{V}$ is adjusted to minimize the power contained in

$$\Phi_{z_n z_n} = |\omega^2|^n \Phi_{zz}$$

Note that the identification task posed here is the mathematical dual of the problem of identifying pilot response behavior. In this case, identification is enhanced by the occurrence of large remnant power and small tracking input power. For zero tracking input, $\Phi_{ZZ}$ is minimized by setting $\hat{V}$=V; that is, perfect identification results. On the other hand, if remnant is zero, $\Phi_{ZZ}$ is minimized by setting $\hat{V} = -1/H$. The prediction that pilot remnant will aid the identification process is consistent with notions of system identification that have appeared in the control literature.

No experimental data were used for this analysis. Instead, tracking "data" were generated by the OCM using nominal values for pilot-related parameters. Analysis was performed in the frequency domain. Parameters of the analysis included plant dynamics, perceptual cues available to the observer, and the order of the internal model adopted by the observer.

Because of the preliminary nature of this modeling effort, the following results are not intended as accurate predictions of a human operator's ability to identify system dynamics, but rather to explore gross trends relating internal models to elements of the task environment.

The results of four tests performed with this approximate model are shown in Figure 5-3. We first describe the test results and then discuss the implications with regard to pilot model development.

To explore the influence of the cueing environment on the operator's internal model of the plant, analysis was performed with error displacement, rate, or acceleration information assumed available to the operator.* The observer was assumed to have a full- (in this case, second-) order model of the plant. Figure 5-3a shows that the transfer function of the identified vehicle dynamics (continuous curves) progressively approached the true plant response (discrete points) as higher-order information was made available.

A subsequent analysis explored the interaction between the available perceptual cues, the order of the observer's internal model, and the identified plant dynamics. Error-rate and error-acceleration cues were considered, as were first- and second-order plant models. Figure 5-3b shows that, with only error-rate available, the order of the internal model had little influence on how accurately the plant transfer function was identified (except at the highest frequencies, where signal power is relatively low). However, when acceleration cues were available (Figure 5-3c), the second-order plant model gave a noticeably closer match to the true plant dynamics.

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*For simplicity, combinations of these cues were not considered, although in practice one would expect a human operator to use all relevant information available.

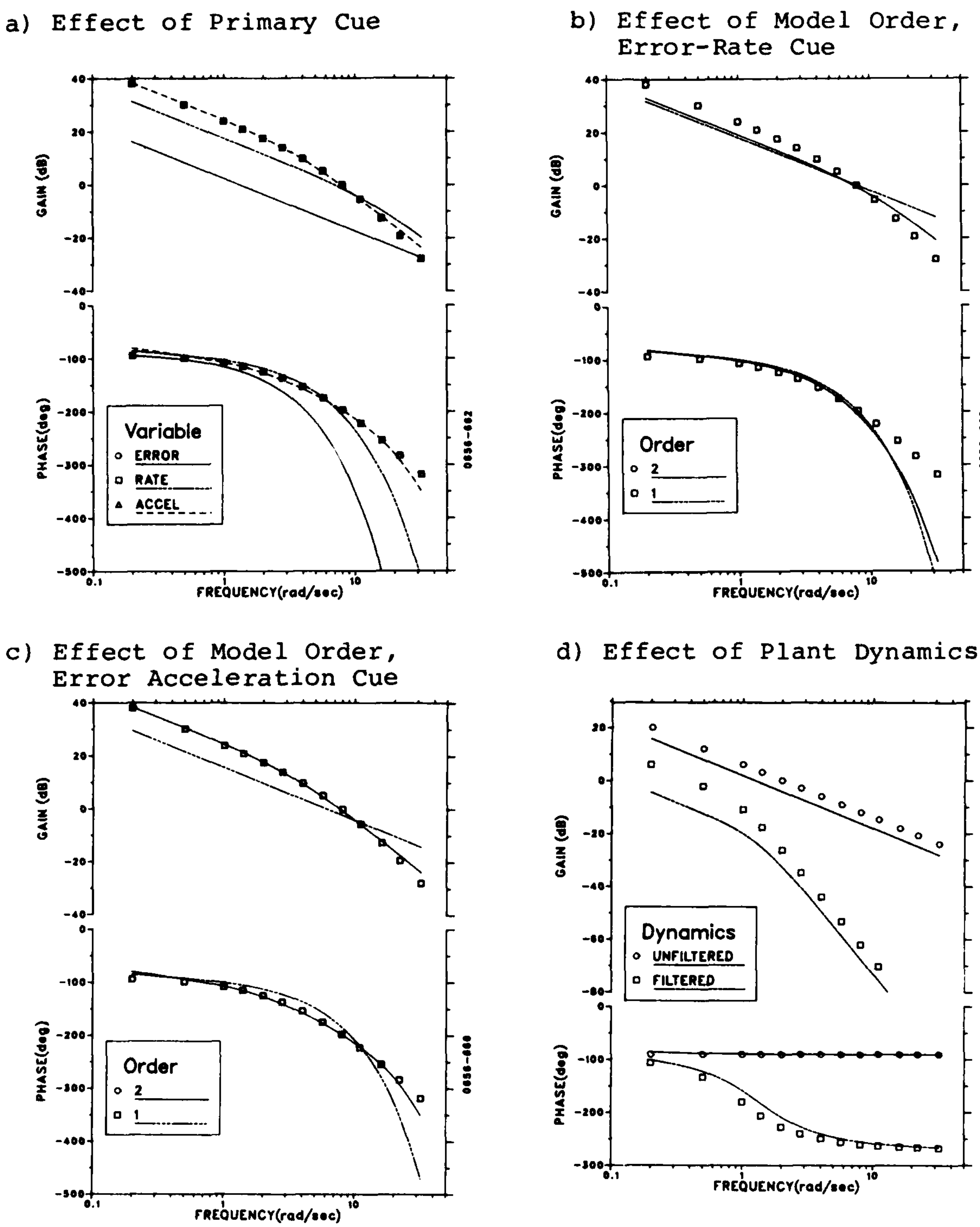


Figure 5-3. Influence of Task Environment on Predicted Internal Model of the Plant

A final test was performed to explore the effects of plant dynamics on the fidelity of the predicted internal plant model. Two sets of plant dynamics were considered: simple rate control (designated as "unfiltered" dynamics in Figure 5-3d), and rate control cascaded with a second-order Butterworth filter having a break frequency of 1 rad/sec ("filtered" dynamics). In each case, the observer was assumed to have an internal model of the appropriate order. Figure 5-3d shows that a qualitatively better estimate of plant dynamics was obtained for the lower-order plant.

The trends revealed by this analytical feasibility study are consistent with the experimental trends reported above: conditions which led to an improvement in the predicted internal model of the plant correspond to experimental conditions that led to an apparent increase in information-processing efficiency. Furthermore, certain cause-and-effect relationships are suggested:

1. The results of Figure 5-3a suggest that the reduced values for pilot-related model parameters associated with whole-body motion cueing are due to improved internal plant model attainable in this cueing environment.

2. Figures 5-3b and 5-3c suggest that learning is more rapid in a motion-base environment partly because the operator is more readily able to determine the correct order of the plant dynamics.

3. Figure 5-3d supports the notion that the apparent degradation in information-processing capabilities associated with high-order plants is, in part, a reflection of a degraded internal model of the task environment.

It must be re-emphasized that the model results summarized in Figure 5-3 are highly qualitative and are intended only to illustrate trends. The intent of this final analysis phase has been to demonstrate the feasibility of considering deficient internal models and of pursuing mechanisms to predict such deficiencies. The preliminary results reported here suggest that such an approach is feasible.

## APPENDIX A

## SUPPLEMENTAL ANALYSIS PERTAINING TO BACKGROUND MATERIAL

This appendix summarizes additional model analysis relevant to the material presented in the background section (Chapter 2). Specifically, differences in time delay and in motor time constant across experimental conditions are explored.

### A.1 Importance of Time Delay Differences

Sensitivity analysis was performed to explore the importance of the differences in the time delays identified for a simple rate-control task (Configuration 2, Table 2-1), and for a task using rate-control cascaded with a low-bandwidth Butterworth filter (Configuration 4, Table 2-1). Time delays were 0.15 and 0.35 seconds, respectively, for these two cases.

Two types of sensitivity analyses were performed. First, the qualitative significance test described in Section 2.2.2 was performed to determine whether or not the observed time delay difference was significant in terms of model-matching error. Matching errors of 14.0 and 7.92 were obtained for the rate- and filtered-rate-control cases, respectively, with all independent parameters adjusted for minimum matching error. A second set of matching errors -- 25.9 and 20.8, respectively -- were obtained for these two cases with time delay fixed at the average value of 0.25 seconds. Matching error ratios of 18.5 and 2.6 were computed from these results, indicating that the task-related change in time delay was "significant" according to the criterion error ratio of 2.0.

The four remaining independent model parameters (two observation noises, motor noise, and motor time constant) were reoptimized during the fixed-delay matching exercises. Thus, the task-related time-delay change cannot be compensated for by readjustments of one or more remaining model parameters.

To explore the potential importance of motivational factors, a second sensitivity test was performed to determine the effect of time delay on tracking error performance for the filtered-rate plant. Error scores were predicted for time delays of 0.15 and 0.35 seconds, with remaining model parameters fixed at the values that provided the best match to the experimental data. The larger delay yielded a predicted rms tracking error score nearly 60% greater than that predicted for the smaller delay. Thus, given the particular model structure applied to this analysis, we fail to support the hypothesis that the larger time delay is due to indifference on the part of the subjects.

### A.2 Analysis of Motor Time Constant Differences

Some of the previous results represented in Table 2-1 were reanalyzed to test the hypothesis that task-related differences in motor time constant reflect the combined effect of a pilot bandwidth limitation plus a true subjective penalty on generating large rates of change of control force. Specifically, the control-rate cost coefficient was assumed to be of the form

$$G = G_o + G_p \qquad \text{(A-1)}$$

where G is the cost coefficient, $G_o$ is the component due to some minimum motor time constant $Tm_o$, and $G_p$ is the component related to physical activity in pounds force per second. The base level $Tm_o$ may be interpreted as a pilot bandwidth limitation, or as the result of a multiplicative motor noise process reflecting, in part, the operator's uncertainties about system response (Levison, 1981; Caglayan and Levison, 1980).

The first test of this hypothesis, applied to data obtained from the Gain/Bandwidth Study of Levison (1971), yielded encouraging results. The first two columns of Table A-1a show values for motor time constant and corresponding control-rate cost (G of Equation A-1) for the simple and filtered rate-control tasks identified as Configurations 2,3, and 4 in Table 2-1. Values shown for G are numerically consistent with the following total performance objective:

$$J = \sigma_e^2 + G \cdot \sigma_{\dot{u}}^2 \qquad \text{(A-2)}$$

where J is the total "cost", $\sigma_e$ the tracking error standard deviation score in degrees visual arc, and $\sigma_{\dot{u}}$ the control-rate standard deviation score in pounds/second of control force.

Because of the nonlinear and plant-dependent relationship between G and Tm it was not feasible to perform a simple regression analysis to find the $Tm_o$ and $G_p$ that would provide the best joint match to the three experimental conditions. Instead, the value $Tm_o$=0.0704 found for the simple rate dynamics was assumed to reflect the intrinsic bandwidth limitation, and $G_p$ was then computed (separately for each plant) as $G - G(Tm_o)$. Columns 4 and 5 of Table A-1a contain values for $G_o$ and $G_p$ identified by this process. Finally, an average value for $G_p$ was obtained by computing the geometric mean of the $G_p$ identified for the two filtered plants, and Equation A-1 was used to "predict" a new value $\hat{G}$ for each plant, using the average $G_p$ and the plant-specific $G_o$.

Comparison of the second and last columns of Table A-1a reveal that the predicted $\hat{G}$ were very close to the corresponding G obtained in the original matching exercise. Recomputation of

Table A-1. Component Analysis of the Motor Time Constant

a) Simple and Filtered Rate Control

| Dynamics | Tm | G | $Tm_o$* | $G_o$ | $G_p$ | $\hat{G}$** |
|---|---|---|---|---|---|---|
| Simple Rate Control | .0704 | 7.74E-3 | .0704 | 7.74E-3 | 0.0 | 8.75E-3 |
| Rate Control + 2 rad/sec filter | .137 | 1.05E-3 | .0704 | 1.57E-5 | 1.03E-3 | 1.03E-3 |
| Rate Control + 1 rad/sec filter | .174 | 9.92E-4 | .0704 | 1.95E-6 | 9.90E-4 | 1.01E-3 |

*By assumption

**Based on $G_p$ = 1.01E-3

b) Rate, Filtered-Rate, and Acceleration Control

| | Tm | G | $Tm_o$* | $G_o$ | $G_p$ | $\hat{G}$** |
|---|---|---|---|---|---|---|
| Simple Rate Control | .0704 | 7.74E-3 | .0704 | 7.74E-3 | 0.0 | 1.27E-2 |
| Rate Control + 1 rad/sec Filter | .174 | 9.92E-4 | .0704 | 1.95E-6 | 9.90E-4 | 4.92E-3 |
| Approximate Acceleration Control | .109 | 2.63E-2 | .0704 | 1.88E-3 | 2.44E-2 | 6.79E-3 |

*By assumption

**Based on Gp = 4.81E-3

model-matching errors using $\hat{G}$ yielded negligible increase over the matching errors obtained with the best-fit G. Thus, the results of this analysis (based on data obtained from a single set of test subjects) support the hypothesis that changes in the identified motor time constants do not reflect differences in information-processing capacity, but rather a combined influence of underlying response bandwidth limitations plus a consistent penalty on generating control activity.

This hypothesis failed for support when the analysis described above was applied to the following set of conditions: (1) simple rate control, (2) rate plus 1 rad/sec Butterworth filter, and (3) approximate acceleration control (Configuration 6 of Table 2-1). The various cost and time-constant parameters identified in this analysis are shown in Table A-1b. Again, the motor time constant found for the rate-control task was taken as the baseline value for $Tm_o$, and non-zero estimates for the physical cost component $G_p$ were derived from data provided by the remaining two tasks. Column 4 of the table shows that the two estimates so obtained differed by more than an order of magnitude.

As before, the geometric mean of the two non-zero estimates of $G_p$ was used to predict new cost weightings $\hat{G}$ for each of the three plants. Unlike the previous analysis, however, these weightings yielded model-matching errors that were "significantly" greater than obtained with the best-fitting weightings. Specifically, matching error ratios (defined in Section 2.2.2) were 1.3, 5.0, and 4.6, respectively for the rate, filtered-rate, and acceleration plants.

Now, there is no guarantee that the value for $Tm_o$ used in this analysis is the optimal value; there may be an alternate choice that provides a better overall match to the collective data.

A small sensitivity analysis indicated, however, that modifying $Tm_o$ would improve the match to a given condition only at the expense of degrading the match to at least one other condition. Therefore it seems unlikely that fixed values can be found for the independent parameters of Equation A-1 that will satisfactorily account for the apparent task-related changes in motor time constant revealed in Table 2-1.

Although the acceleration-control data were obtained in a different experiment (performed by a different experimenter) than the rate and filtered-rate data, there was considerable commonality across the experiments:

1. Error was indicated by translation of an electronically-presented error indicator referenced to an electronically-presented zero indicator.
2. Controls were hand-operated and nearly isometric.
3. Subjects were well-trained, and were all instructed to minimize mean-squared error.

While some differences in performance capabilities would be expected from different subject populations, an order of magnitude difference in the subjective penalty assigned to rate of change of control does not seem reasonable on this basis alone. Thus, we tentatively conclude that (1) some other combination of bandwidth and physical constraints will match the data base, or that (2) apparent task-related changes in the motor time constant parameter reflect some other factor limiting perceptual-motor performance that is not directly accounted for in our modeling philosophy.

## APPENDIX B
## SUPPLEMENTAL ANALYSIS CONCERNING EFFECTS OF PRACTICE

Additional experimental and model results relating to practice effects are presented in this Appendix. A description of the data base and a summary of experimental and model results may be found in Chapter 3.

### B.1 Effects of Practice on Frequency Response

Experimental and model results are presented as follows for individual subjects:

Figure B-1 (5 parts): static group, stable-plant study.
Figure B-2 (4 parts): motion group, stable-plant study.
Figure B-3 (6 parts): unstable-plant study

Describing function data are plotted only where signal/noise considerations indicate that the data are reliable (Levison, 1971). Consequently, some of the curves pertaining to early practice conditions span a relatively restricted frequency range.

a) Subject CP

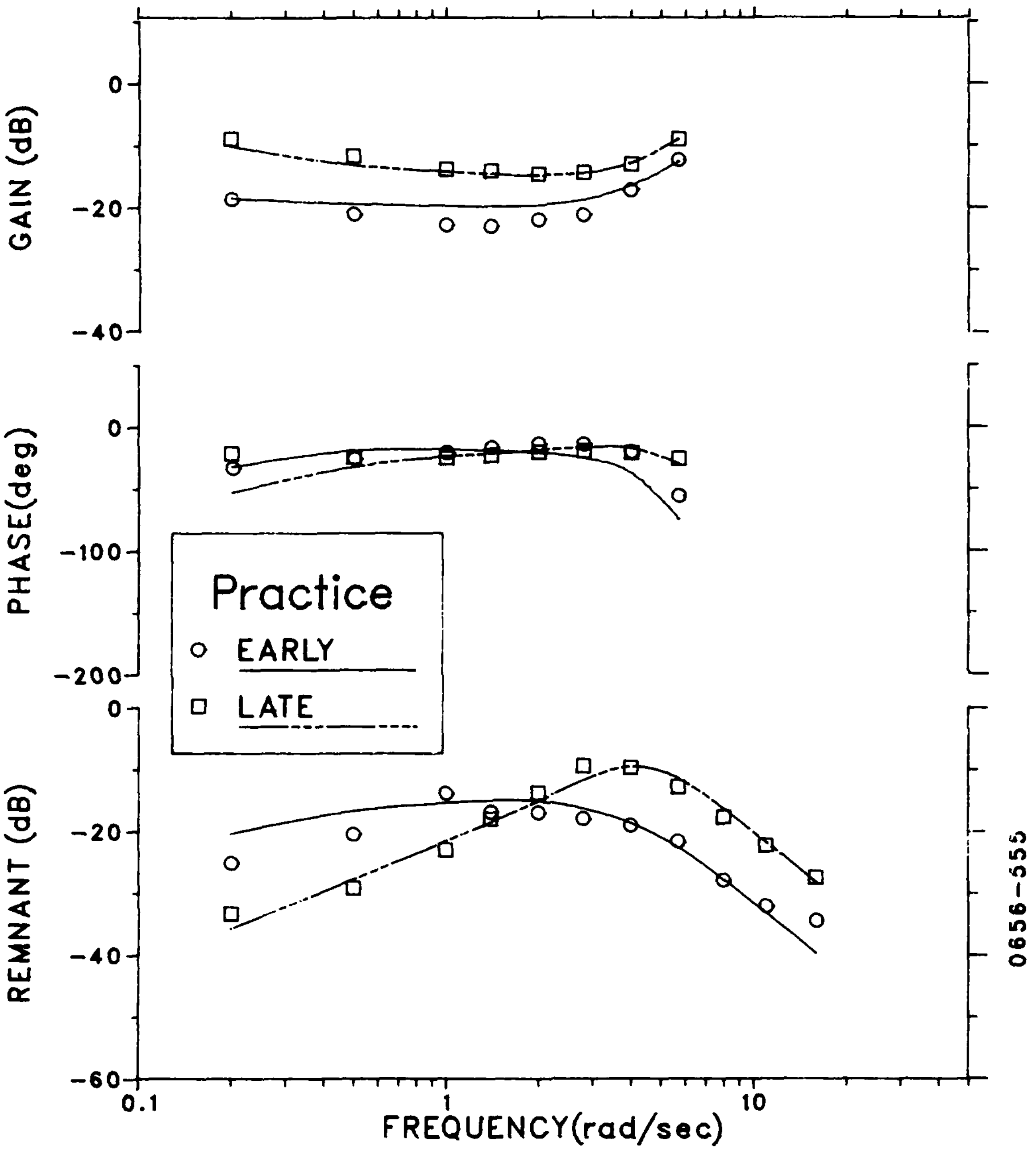


Figure B-1. Effects of Practice on Pilot Frequency Response: Static Group, Stable Plant Study

b) Subject DC

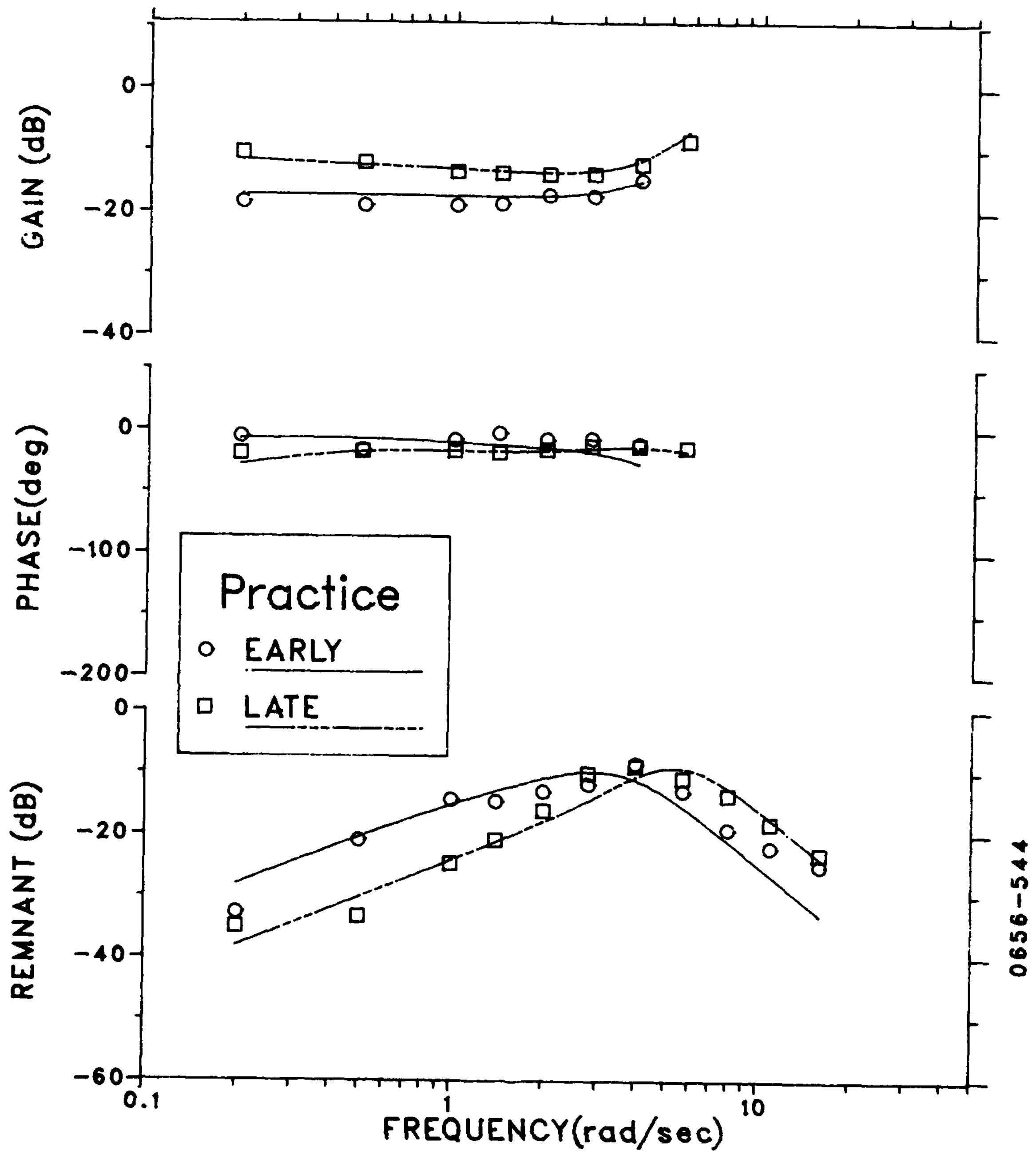


Figure B-1. (Cont'd)

c) Subject DS

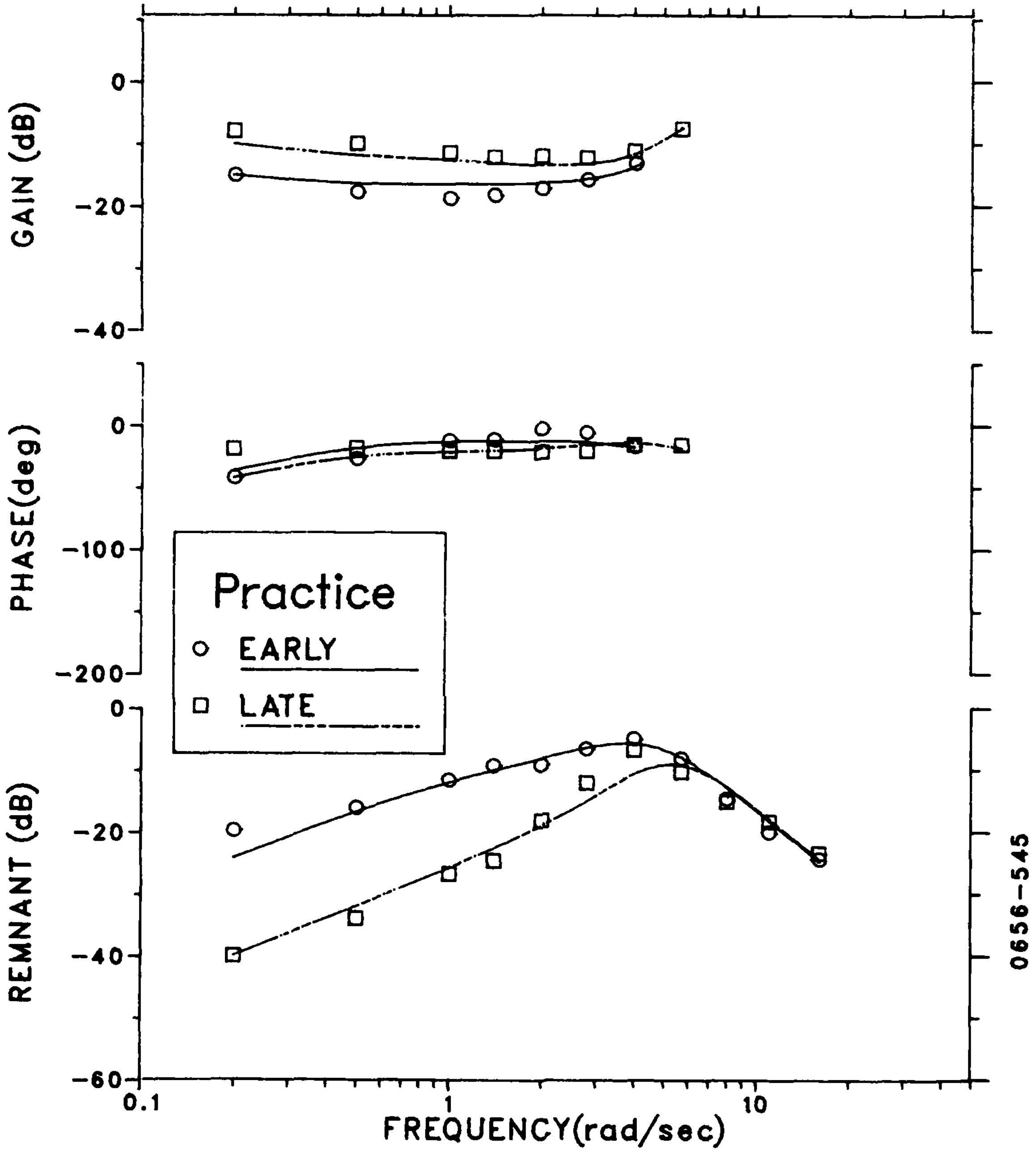


Figure B-1. (Cont'd)

d) Subject TB

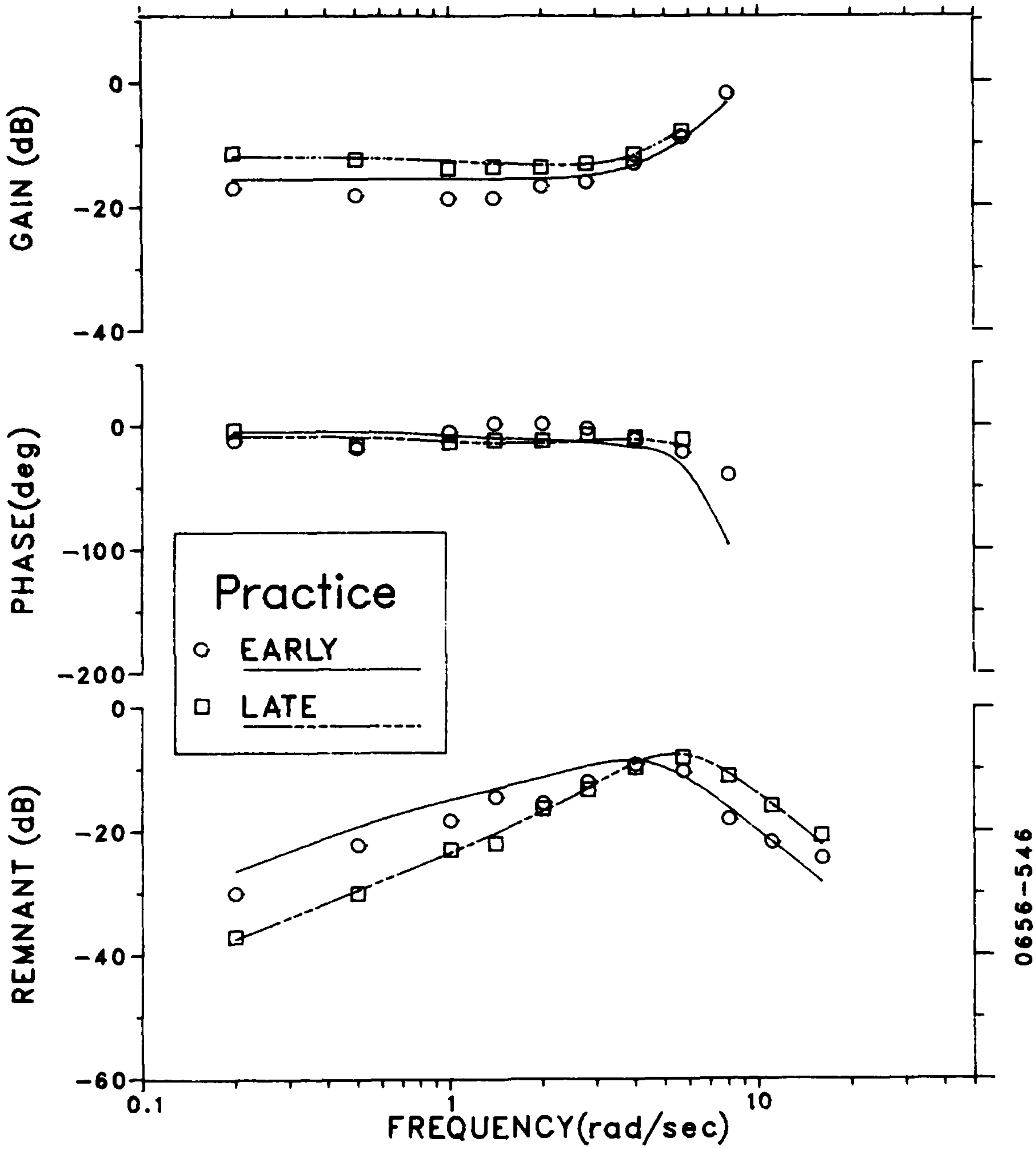


Figure B-1. (Cont'd)

e) Subject VS

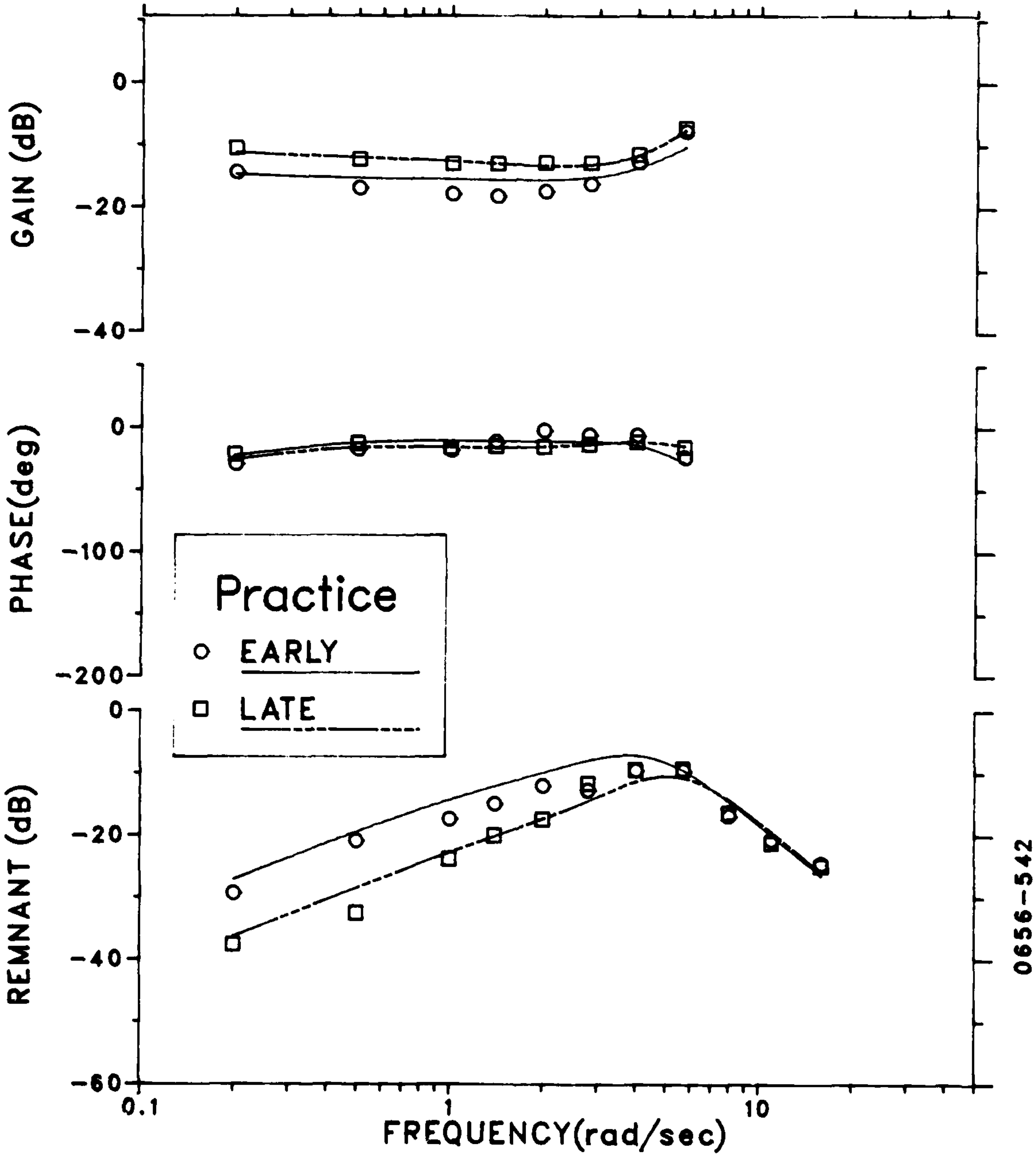


Figure B-1. (Concluded)

a) Subject CP

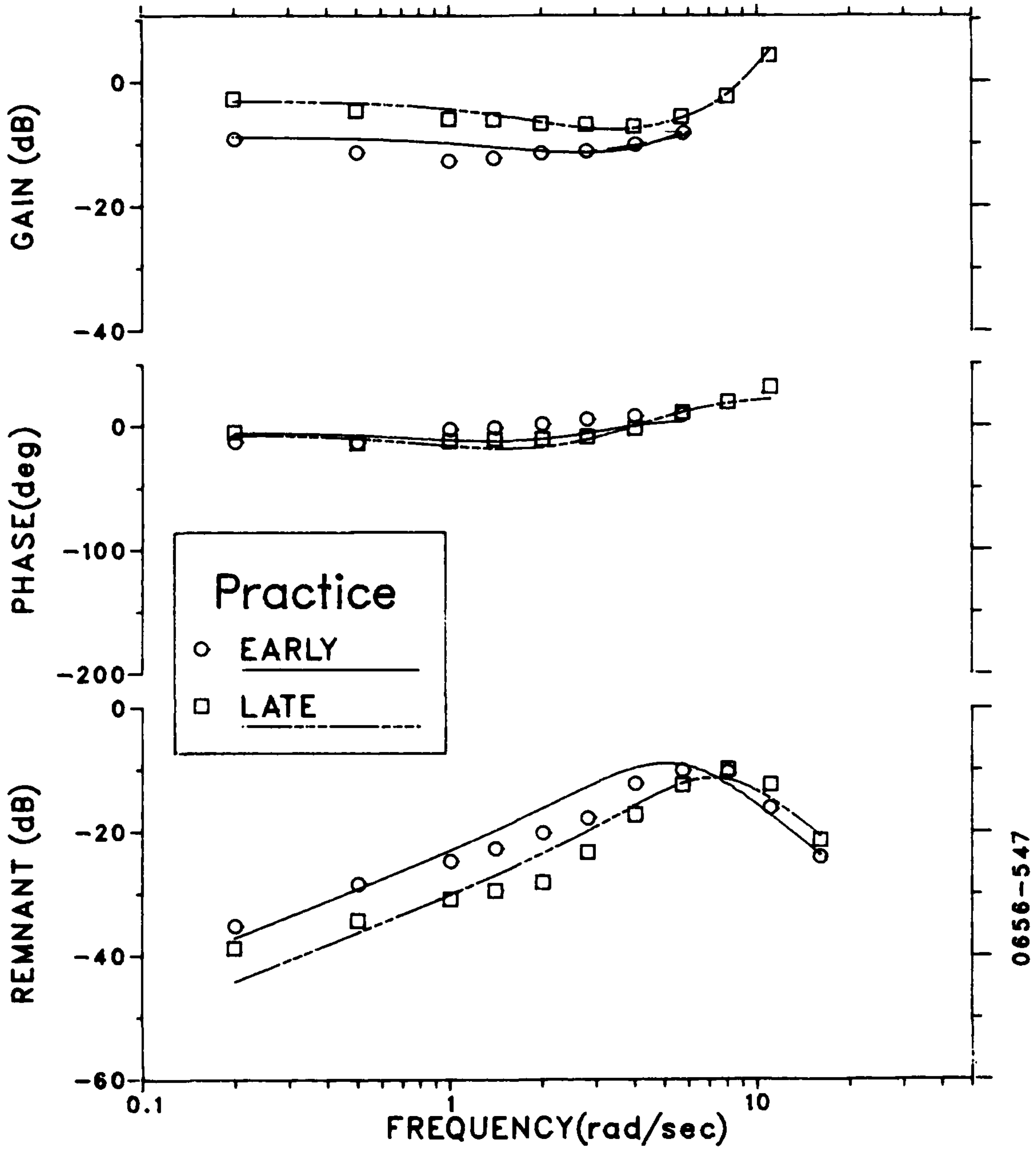


Figure B-2. Effects of Practice on Pilot Frequency Response: Motion Group, Stable Plant Study

b) Subject DM

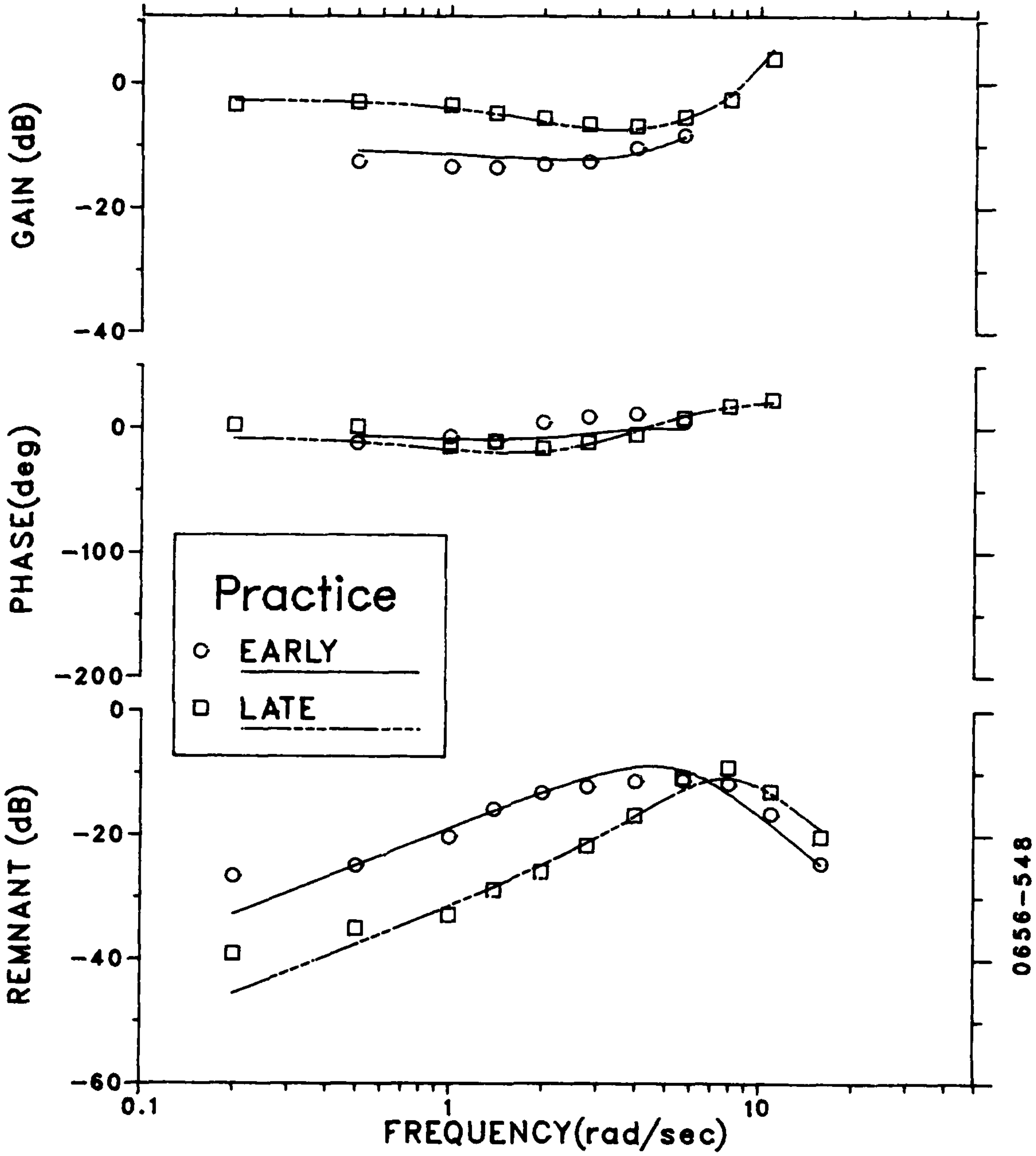


Figure B-2. (Cont'd)

c) Subject ML

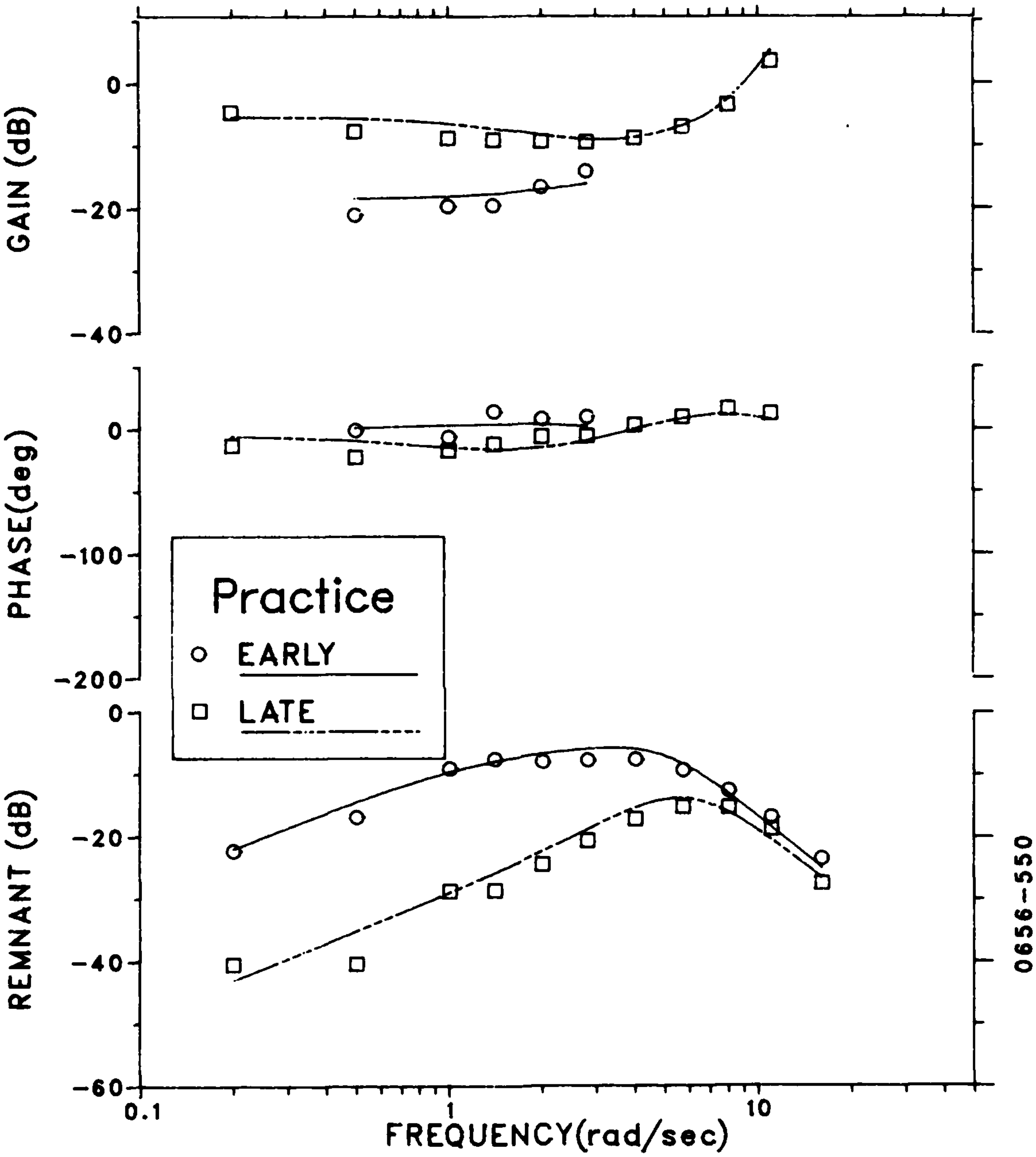


Figure B-2. (Cont'd)

d) Subject RK

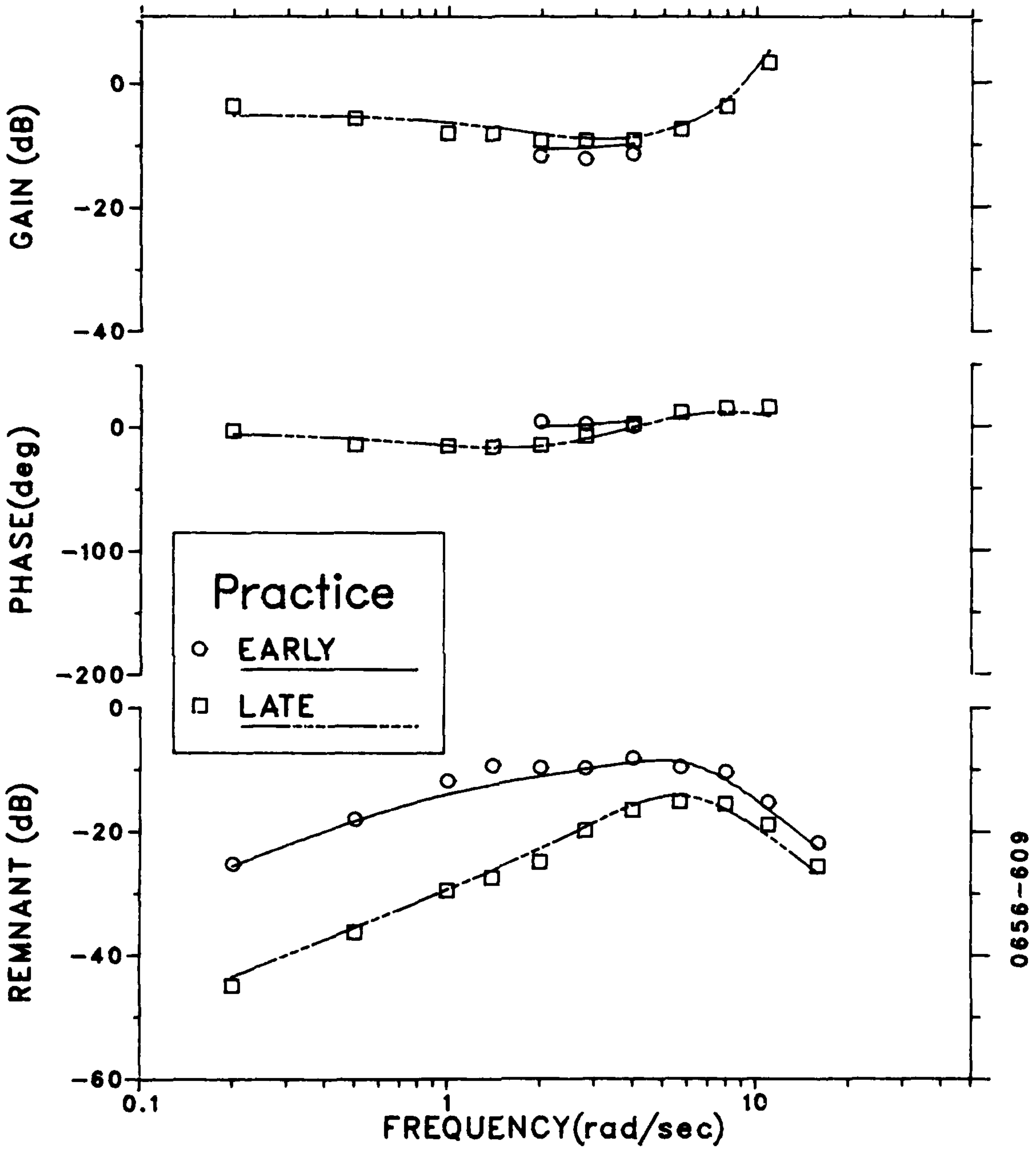


Figure B-2. (Concluded)

a) Subject DMI

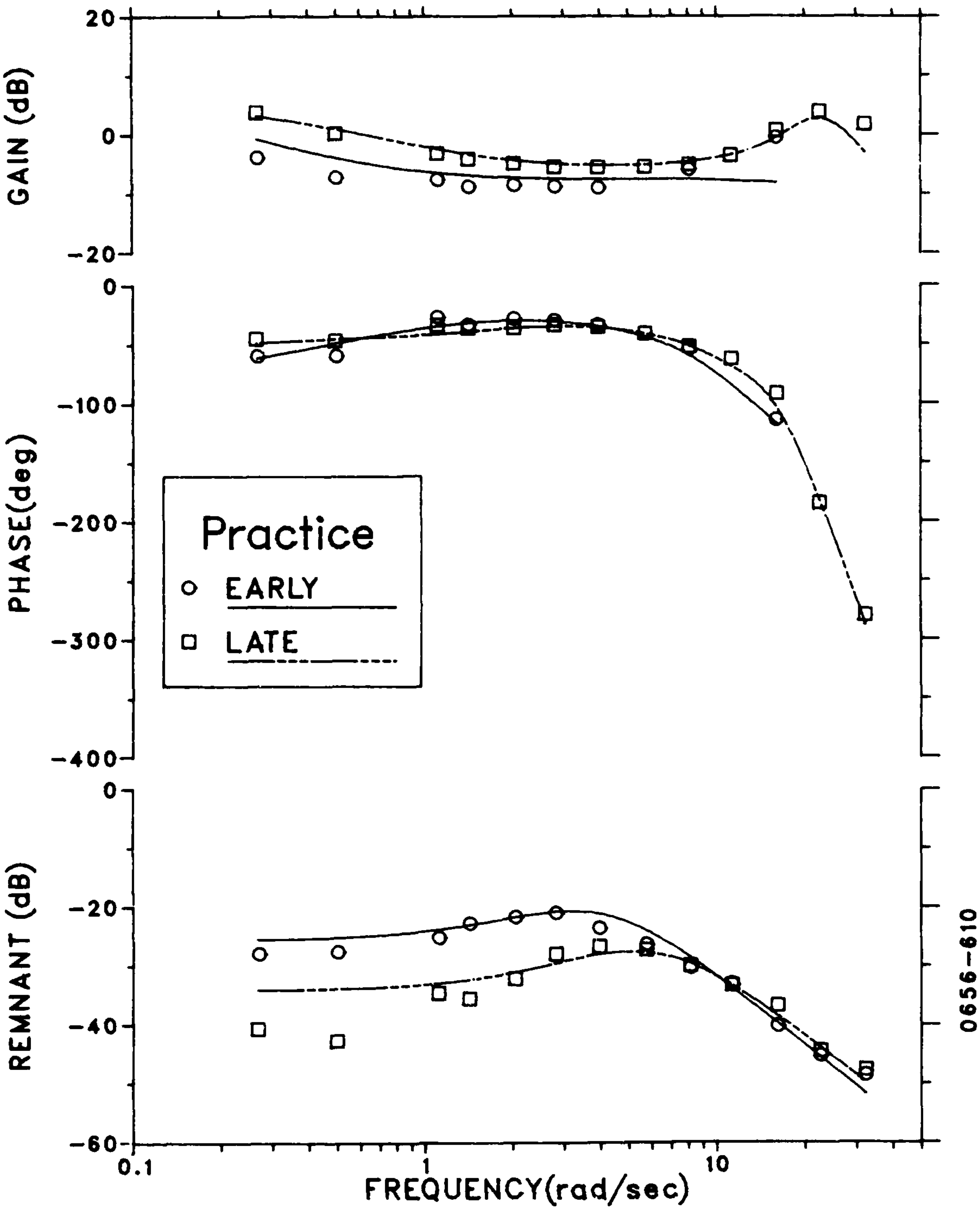


Figure B-3. Effects of Practice on Pilot Frequency Response: Unstable Plant Study

b) Subject KDH

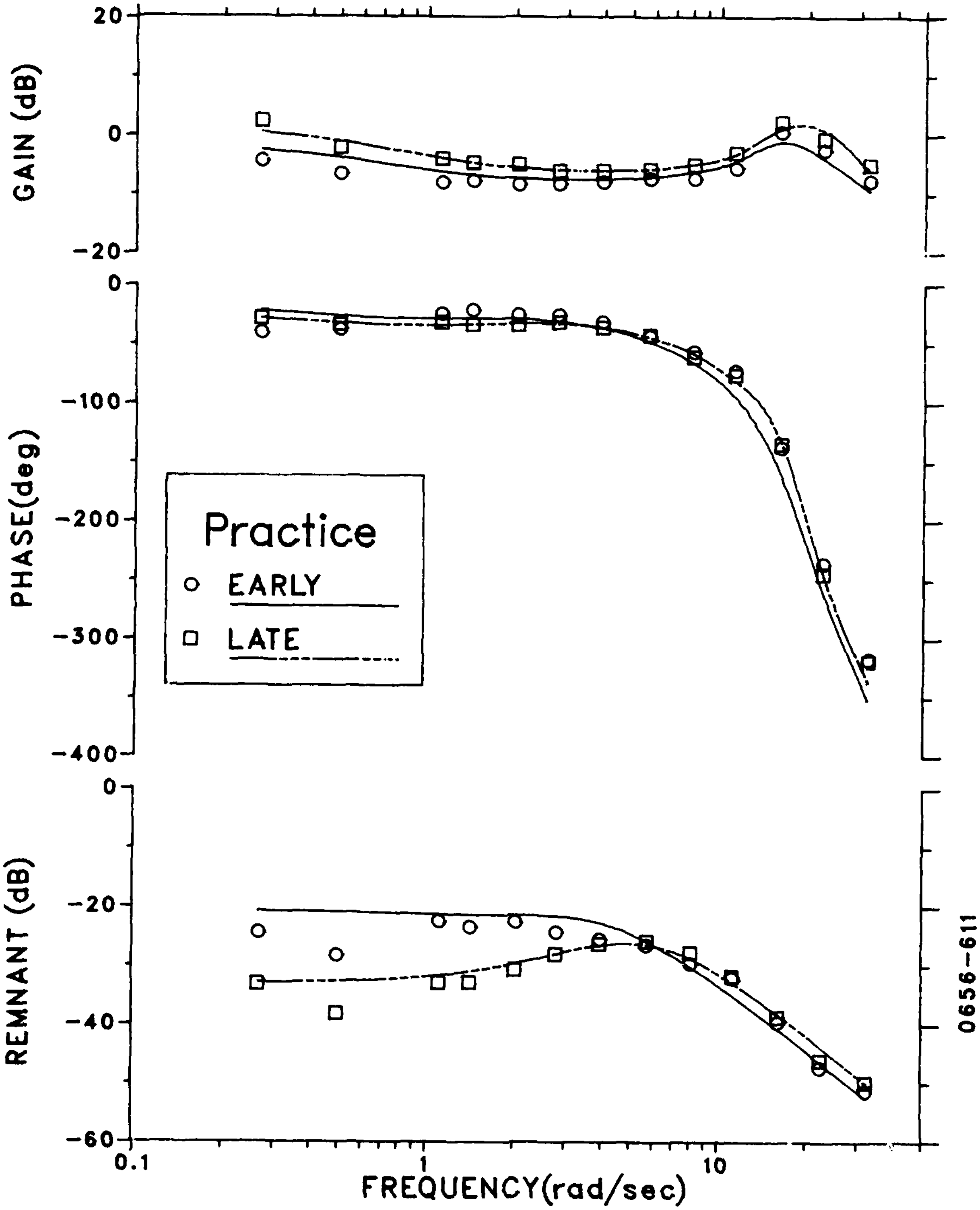


Figure B-3. (Cont'd)

c) Subject KJW

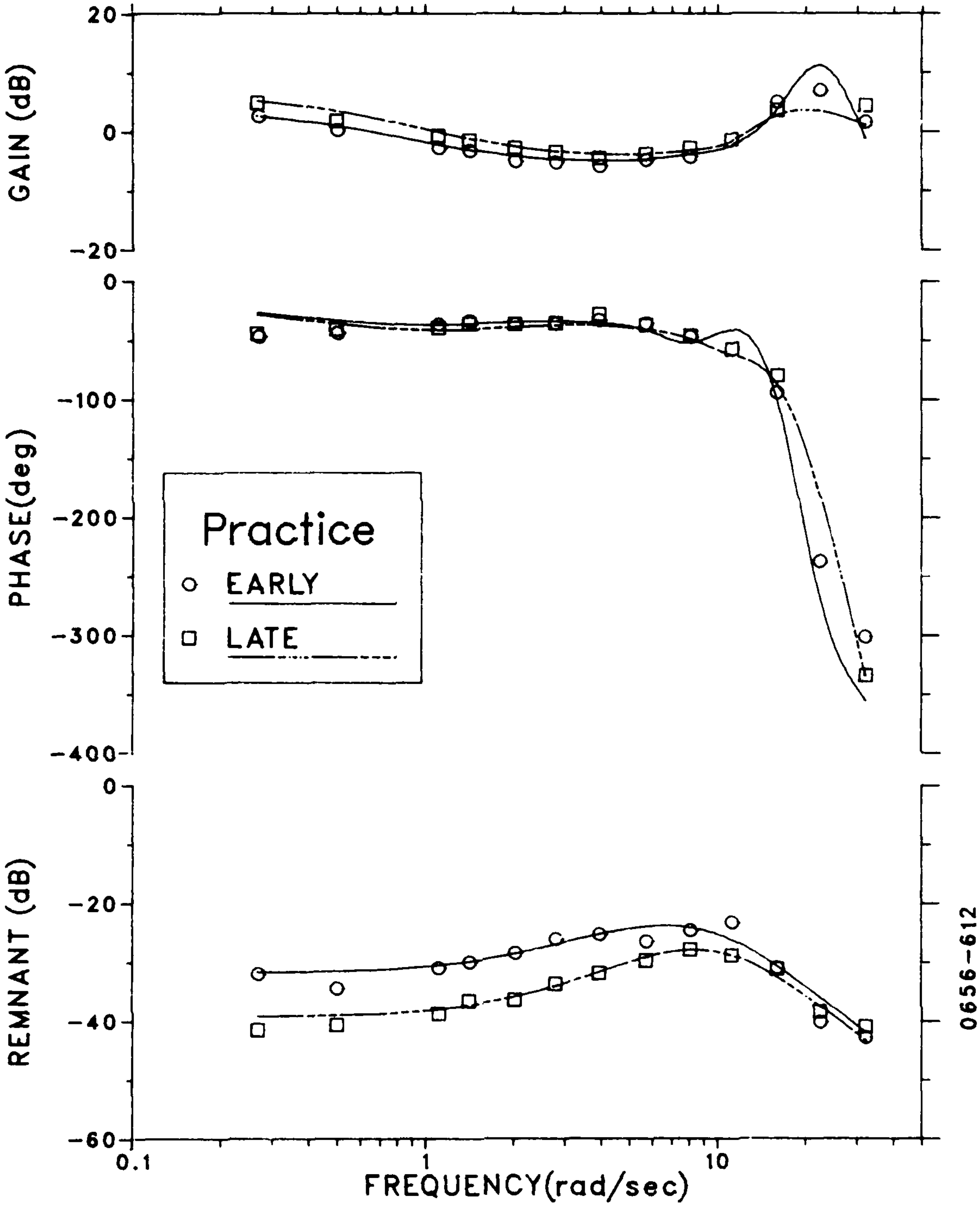


Figure B-3. (Cont'd)

d) Subject LEK

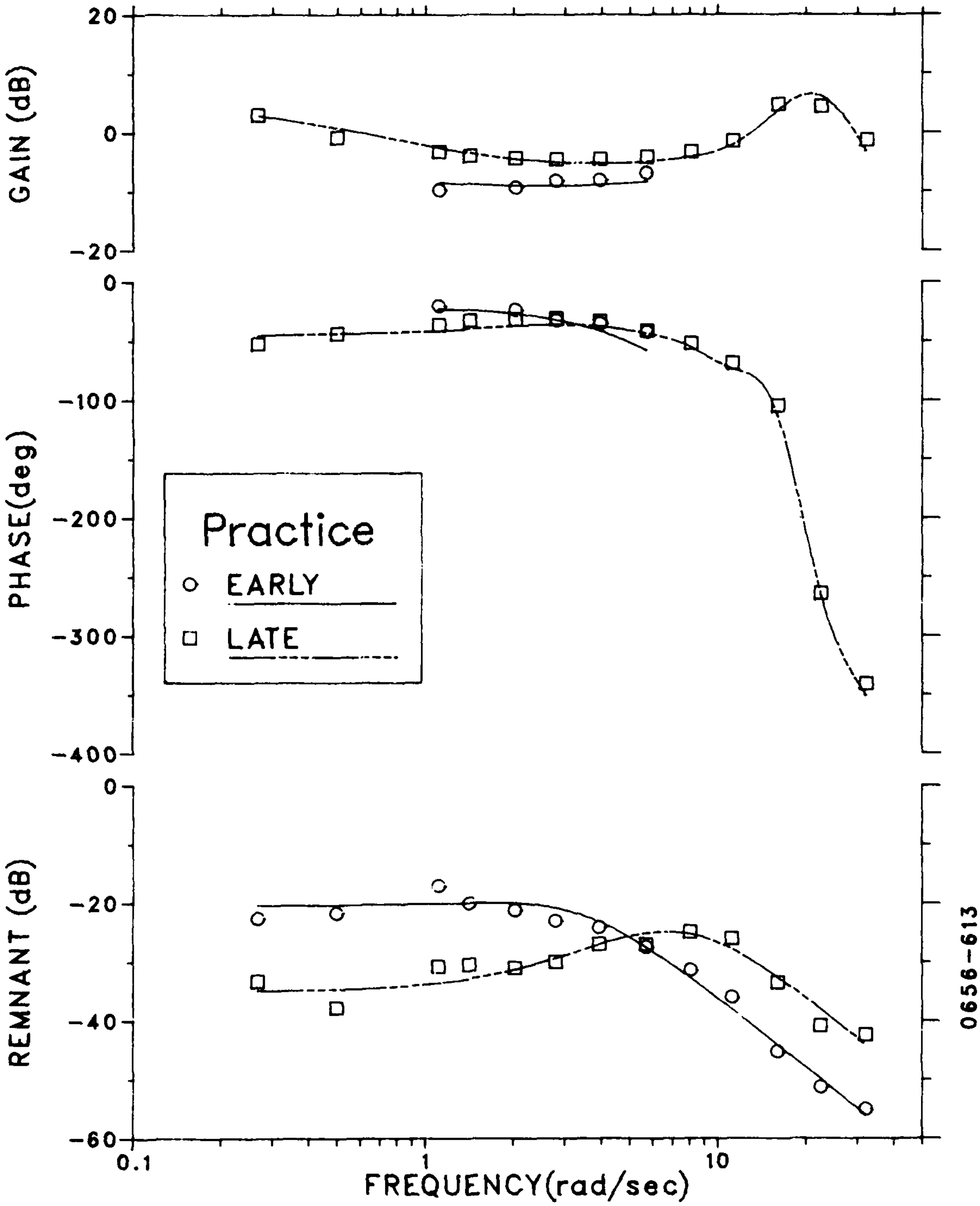


Figure B-3. (Cont'd)

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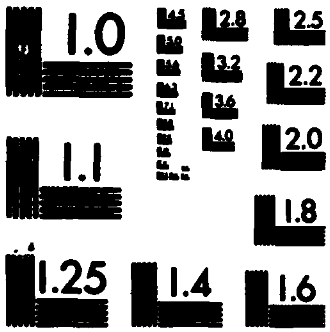


MICROCOPY RESOLUTION TEST CHART
NATIONAL BUREAU OF STANDARDS-1963-A

e) Subject SAH

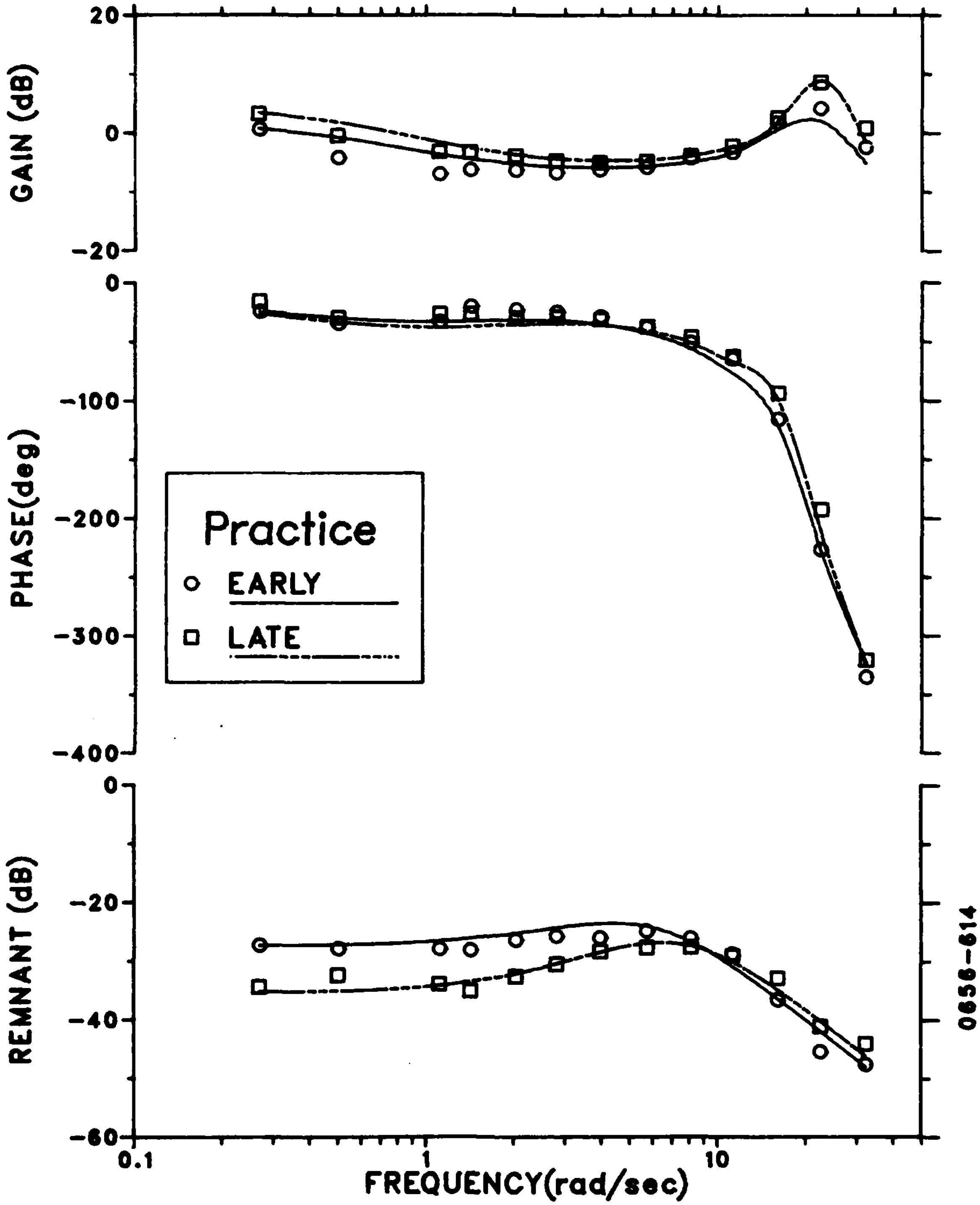


Figure B-3. (Cont'd)

f) Subject TMV

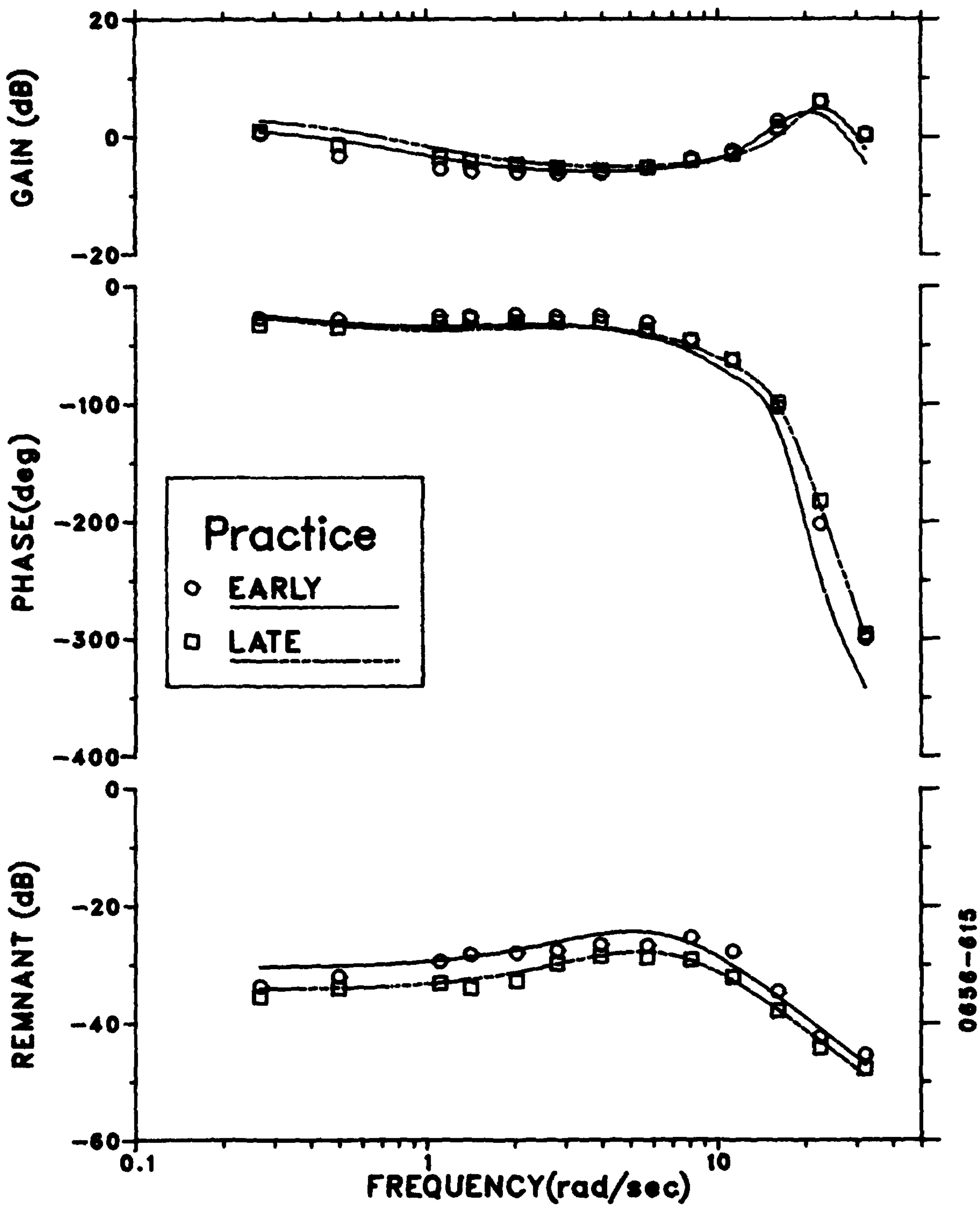


Figure B-3. (Concluded)

## B.2 Effects of Practice on Independent Model Parameters

Tables B-1 and B-2 contain model parameters identified via the unconstrained and constrained search procedures, respectively, for the stable-plant study. Population means and standard deviations are shown along with data for individual subjects.

Parameters for subjects participating in the unstable-plant study are given in Table B-3 for the unconstrained search. (The constrained search performed on the unstable-plant data was performed on the population means only, not on data obtained from individual subjects.) The rows designated as "average" contain the parameters identified from the ensemble-averaged data, as contrasted with the means of the parameters identified for individual subjects.

Table B-1. Pilot Parameters Identified from the Stable-Plant Data: Unconstrained Search

| | Parameter | | | | | |
|---|---|---|---|---|---|---|
| Subject | Pe | $P\dot{e}$ | $P\ddot{e}$ | Pm | Td | Tm |
| **a) Static Group, Early** | | | | | | |
| CP | - 5.6 | -18.7 | -- | -27.0 | .235 | .345 |
| DC | -14.0 | -14.7 | -- | -49.5 | .169 | .220 |
| DS | -10.0 | -14.0 | -- | -36.8 | .182 | .145 |
| TB | -10.8 | -16.0 | -- | -55.6 | .198 | .162 |
| VS | -11.9 | -14.5 | -- | -40.6 | .152 | .152 |
| MEAN | -10.5 | -15.6 | -- | -41.9 | .187 | .205 |
| STD DEV | 3.1 | 1.9 | -- | 11.1 | .032 | .084 |
| **b) Static Group, Late** | | | | | | |
| CP | -21.6 | -16.3 | -- | -29.4 | .161 | .169 |
| DC | -24.0 | -21.1 | -- | -41.0 | .280 | .127 |
| DS | -25.4 | -17.6 | -- | -35.9 | .206 | .131 |
| TB | -21.3 | -17.3 | -- | -56.5 | .218 | .112 |
| VS | -20.3 | -21.2 | -- | -40.3 | .238 | .138 |
| MEAN | -22.5 | -18.7 | -- | -40.6 | .221 | .135 |
| STD DEV | 2.1 | 2.3 | -- | 10.1 | .044 | .021 |
| **a) Motion Group, Early** | | | | | | |
| CF | -23.3 | -14.2 | -20.3 | -60.0 | .200 | .112 |
| DM | -16.4 | -16.5 | -18.6 | -60.0 | .200 | .122 |
| ML | - 8.4 | -10.8 | -16.4 | -60.0 | .200 | .141 |
| RK | - 5.3 | -14.9 | -22.6 | -60.0 | .200 | .109 |
| MEAN | -13.4 | -14.1 | -19.5 | -60.0 | .200 | .121 |
| STD DEV | 8.1 | 2.4 | 2.6 | -- | -- | .015 |
| **b) Motion Group, Late** | | | | | | |
| CF | -30.7 | -18.4 | -25.4 | -60.0 | .200 | .0838 |
| DM | -32.4 | -19.8 | -25.1 | -60.0 | .200 | .0770 |
| ML | -32.8 | - 8.7 | -24.4 | -60.0 | .200 | .119 |
| RK | -33.6 | - 7.8 | -24.7 | -60.0 | .200 | .118 |
| MEAN | -32.4 | -13.7 | -24.9 | -60.0 | .200 | .0995 |
| STD DEV | 1.2 | 6.3 | 4.4 | -- | -- | .0222 |

Table B-2. Pilot Parameters Identified from the Stable-Plant Data: Constrained Search

| Subject | Parameter | | | |
|---|---|---|---|---|
| | Pe=Pė | Pm | Td | Tm |

a) Static Group, Early

| | | | | |
|---|---|---|---|---|
| CP | -17.0 | -29.0 | .200 | .342 |
| DC | -15.5 | -45.0 | .200 | .221 |
| DS | -13.0 | -36.0 | .200 | .145 |
| TB | -15.5 | -56.0 | .200 | .162 |
| VS | -15.0 | -40.0 | .200 | .152 |
| MEAN | -15.2 | -41.2 | .200 | .204 |
| STD DEV | 1.4 | 10.1 | -- | .083 |

b) Static Group, Late

| | | | | |
|---|---|---|---|---|
| CP | -19.0 | -29.0 | .200 | .170 |
| DC | -18.5 | -45.0 | .200 | .125 |
| DS | -20.0 | -36.0 | .200 | .130 |
| TB | -17.5 | -56.0 | .200 | .112 |
| VS | -19.5 | -40.0 | .200 | .138 |
| MEAN | -18.9 | -41.2 | .200 | .135 |
| STD DEV | 1.0 | 10.1 | -- | .022 |

c) Motion Group, Early

| | | | | |
|---|---|---|---|---|
| CF | -18.5 | -60.0 | .200 | .112 |
| DM | -17.5 | -60.0 | .200 | .122 |
| ML | -11.0 | -60.0 | .200 | .145 |
| RK | -14.5 | -60.0 | .200 | .120 |
| MEAN | -15.4 | -60.0 | .200 | .124 |
| STD DEV | 3.4 | -- | -- | .015 |

d) Motion Group, Late

| | | | | |
|---|---|---|---|---|
| CF | -24.5 | -60.0 | .200 | .0836 |
| DM | -24.5 | -60.0 | .200 | .0770 |
| ML | -23.5 | -60.0 | .200 | .119 |
| RK | -24.0 | -60.0 | .200 | .118 |
| MEAN | -24.1 | -60.0 | .200 | .0994 |
| STD DEV | 0.5 | -- | -- | .0222 |

Table B-3. Pilot Parameters Identified from the Unstable-Plant Data

| | Parameter | | | | |
|---|---|---|---|---|---|
| Subject | Pe | Pė | Pm | Td | Tm |
| **a) Early** | | | | | |
| DMI | -17.2 | -15.7 | -25.7 | .0809 | .118 |
| KDH | -15.0 | -21.3 | -44.7 | .152 | .128 |
| KJW | -20.6 | -21.9 | -51.5 | .156 | .0633 |
| LEK | -16.3 | -18.8 | -47.9 | .175 | .141 |
| SAH | -17.9 | -21.0 | -47.4 | .136 | .0921 |
| TMV | -20.7 | -21.6 | -47.9 | .147 | .0853 |
| MEAN | -18.0 | -20.0 | -44.2 | .141 | .105 |
| STD DEV | 2.3 | 2.4 | 9.3 | .032 | .029 |
| AVERAGE | -16.9 | -19.9 | -45.3 | .131 | .089 |
| **b) Late** | | | | | |
| DMI | -23.4 | -22.1 | -31.1 | .117 | .0933 |
| KDH | -25.1 | -21.7 | -41.0 | .143 | .0990 |
| KJW | -26.3 | -23.2 | -50.0 | .141 | .0604 |
| LEK | -24.7 | -21.2 | -36.7 | .151 | .0721 |
| SAH | -23.7 | -22.4 | -48.2 | .136 | .0741 |
| TMV | -22.5 | -22.7 | -46.1 | .123 | .0862 |
| MEAN | -24.3 | -22.2 | -42.2 | .135 | .0809 |
| STD DEV | 1.4 | 0.7 | 7.3 | .013 | .0145 |
| AVERAGE | -23.8 | -22.0 | -43.6 | .135 | .0783 |

## B.3 Effects of Search Constraint on Matching Error

Model parameters were initially identified without constraints (other than the constraint that all parameters be numerically positive). Data from the stable-plant study were subsequently re-analyzed subject to two levels of constraint. For constraint conditions C1, time delay was fixed at 0.2 seconds for all subjects. The motor noise/signal ratio was fixed for each static-group subject at the average of the early and late values previously identified; whereas the motor noise/signal ratio was fixed at -60 dB for all motion-group subjects. Constraint level C2 included the constraints of C1, plus the additional constraint that a single observation noise/signal ratio be applied to all observational variables (i.e., $P_e = P_{\dot{e}}$ for the static group, $P_e=P_{\dot{e}}=P_{\ddot{e}}$ for the motion group).*

Table B-4 shows matching errors along with matching error ratios relative to the unconstrained error, for the subjects participating in the stable-plant study. Matching error ratios are absent for one case -- Subject ML, motion group, early practice -- because of a failure for the OCM algorithms to converge during the unconstrained search. All calculations were performed on three-place numbers and then rounded off to two digits for presentation.

A certain amount of caution should be exercised when interpreting the matching errors shown in Table B-4, as these errors are determined by the variability in the data as well as by the actual degree of mismatch (see Section 2.2.2). Nevertheless, the larger errors shown for the early-practice condition confirm

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*Because the quasi-Newton search routine implemented at the time of this analysis did not specifically allow the user to constrain all noise/signal ratios to a single value, the C2 search (a 2-parameter search) was performed manually. Hence, values for noise/signal ratio shown in Table B-2 are quantized to the nearest 0.5 dB.

Table B-4. Effects of Search Constraints on Matching Error

| Subject | Constraint* | Early Matching Error Actual | Early Matching Error Ratio | Late Matching Error Actual | Late Matching Error Ratio |
|---|---|---|---|---|---|
| **a) Static Group, Stable-Plant Study** | | | | | |
| CP | U | 38 | -- | 7.4 | -- |
| | C1 | 40 | 1.0 | 7.8 | 1.1 |
| | C2 | 42 | 1.1 | 9.1 | 1.2 |
| DC | U | 18 | -- | 9.1 | -- |
| | C1 | 18 | 1.0 | 10 | 1.1 |
| | C2 | 19 | 1.1 | 12 | 1.3 |
| DS | U | 1.8 | -- | 8.1 | -- |
| | C1 | 1.9 | 1.0 | 8.1 | 1.0 |
| | C2 | 3.6 | 2.0 | 12. | 1.5 |
| TB | U | 19 | -- | 2.6 | -- |
| | C1 | 20 | 1.0 | 2.6 | 1.0 |
| | C2 | 21 | 1.1 | 3.8 | 1.5 |
| VS | U | 13 | -- | 4.1 | -- |
| | C1 | 14 | 1.0 | 4.3 | 1.0 |
| | C2 | 16 | 1.2 | 4.4 | 1.1 |
| **b) Motion Group, Stable-Plant Study** | | | | | |
| CF | U | 17 | -- | 6.2 | -- |
| | C1 | 17 | 1.0 | 6.2 | 1.0 |
| | C2 | 18 | 1.1 | 7.0 | 1.1 |
| DM | U | 7.5 | -- | 6.6 | -- |
| | C1 | 7.5 | 1.0 | 6.6 | 1.0 |
| | C2 | 8.5 | 1.1 | 8.5 | 1.3 |
| ML | U | -- | -- | 11 | -- |
| | C1 | 14 | -- | 11 | 1.1 |
| | C2 | 17 | -- | 14 | 1.3 |
| RK | U | 6.2 | -- | 5.5 | -- |
| | C1 | 12 | 2.0 | 6.2 | 1.1 |
| | C2 | 33 | 5.3 | 8.2 | 1.5 |

*Constraints were as follows:

U: unconstrained

C1: Time delay fixed at 0.2 seconds, all runs. Motor noise/signal ratio fixed at average of early and late for static group, -60 dB for motion group.

C2: Same as C1, plus $P_e = P_{\dot{e}}$ for static group, $P_e = P_{\dot{e}} = P_{\ddot{e}}$ for motion group.

the subjective impressions obtained from visual inspection of Figures B-1 and B-2; namely, that the OCM tended to provide a better match to the data obtained late in the training phase.

Table B-4 shows that in 16 out of 17 cases, the C1 constraint (fixed delay and motor noise/signal ratio) increased the matching error ratio by less than 15%. A two-fold increase was found for the remaining case (RK, motion group, early), but the relative lack of valid describing function data (see Figure B-2d) for this condition renders the model-match suspect. In summary, fixing time delay and motor noise/signal ratio had no significant influence on model-matching error, and model analysis made with this constraint was justified.

Constraining observation noise/signal ratios to be uniform across perceptual variables tended to degrade the matching error by a greater amount, but generally not enough to be "significant" according to the error ratio criterion of 2.0. Table B-4 shows that this constraint yielded a matching error ratio of under 1.25 for about half the cases, over 2.0 in only two cases.

T-tests were performed on paired differences between error and error-rate noise/signal ratios for the stable-plant (static group only) and performance-analyzer subject populations. A weak significance level (alpha=.05) was found for the performance-analyzer subjects late in training; no significance (alpha less than 0.05) was found for the remaining three tests.

The results of the significance tests, therefore, generally justify the uniform-ratio constraint applied to this data base. Nevertheless, the noise ratio differences did show consistent trends. With few exceptions, the noise/signal ratios associated with perception of error were greater than error-rate noise/signal ratios early in training, whereas the reverse trend was found in the data obtained late in training.

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